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Farm Productivity Gains in the European Union
a Microeconomic Analysis

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Preface

Dear reader,

The work lying in front of you is the outcome of many interesting months full of effort, curiosity, passion, wonderment, perseverance, setbacks, breakthroughs and surprises. It has been quite an experience to end my study career as a student bioengineer at the AGRO faculty with. At the start of this master thesis more than one year ago, the domain of productivity analysis and programming in Stata was quite new to me. However, I soon got cracking at it and, little by little, the pieces started falling together. Although this project never escaped my mind, this final year has really flown by and it has left me with a very satisfied feeling.

In this preface, I would like to take advantage of the opportunity to express my gratitude towards several people helping me achieving this. First things first: many, many thanks go to my promoter, Professor Bruno Henry De Frahan, who spend endless hours teaching, guiding, helping, counselling and supporting me. No question was ever asked to much for him and without his knowledge and attitude, this work would never have come this far. I sincerely liked working with him.

Furthermore, I wish to thank everyone else who supported me and helped me achieving this work in one way or another. Hereby I think, amongst others, especially of my family, my girlfriend, members of the department of Rural Economy (ECRU) and the readers of this thesis.

It has been quite a year, but in the end I'm very pleased with my achievements. I feel as if I can be proud of the tiny contribution I've made to the fascinating (but not self-evident) world of productivity analysis.

Ruben Klaasen

June 2018

Abstract

Throughout this work, we develop a microeconomic framework for estimating a theoretically consistent, well-behaved, multi-input, multi-output cost function, according to a flexible Symmetric Generalized McFadden (SGM) functional form. Hence, several productivity-related indicators can be computed for their use in a profound productivity analysis. The capabilities of this framework are illustrated by an analysis of the productivity gains achieved by the crop farms located in the three most important regions for cereal production in the European Union, i.e., West and Central France and Central Spain, using microeconomic data obtained by the EU-Farm Accountancy Data Network (EU-FADN) during the period 1989 – 2011. The analysis reveals considerable differences across these regions, mainly regarding their evolutionary patterns. In particular, the regions of West France and Central Spain exhibit an alarming downward sloping trend in their rates of cost diminution and technical change. In a final stage, we attempt to identify several determinants underlying the estimated productivity gains by establishing several correlation-coefficients. We find that a larger farm size does not necessarily attribute to higher productivity gains. Also, higher degrees of farm specialization and land ownership are positively correlated with productivity gains in all investigated regions, whereas a negative correlation is found for the yields of cereal production. Finally, we note that productivity indicators can differ significantly amongst subregions and that a positive correlation can be established between output prices and farm productivity gains, with an exception for the region of West France.

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1. Introduction

1.1. Context

This work represents a master thesis conducted in order to obtain the degree of master bio-engineer in agronomic sciences, specialized in agricultural economics and natural resources at the Catholic University of Louvain, Belgium. The overall objective throughout this study is to develop a framework for estimating a flexible and theoretically consistent multi-output multi-input cost function, according to the Symmetric Generalized McFadden (SGM) functional form. Such estimation allows to derive total, average and marginal cost functions for individual farm output categories as well as input demand functions for individual farm input categories, an information seldom directly available from the common databases. The empirical part of this work applies this framework to estimate cost functions of European crop farms, using data obtained by the EU-Farm Accountancy Data Network, or EU-FADN. Using these estimates, we are able to construct several indicators at the farm level to assess the possible occurrence of productivity gains. Our study is framed within several preceding works conducted by, for instance, Henry de Frahan, Dong & De Blander (2015), as reported in the MIMO Deliverable 8, and De Blander, Henry de Frahan & Offerman (2011), as reported in the FACEPA Deliverable 9.1. Other publications that have used (a variation to) this framework, are Wieck & Heckelei (2007) and Henry de Frahan, Baudry, De Blander, Polomé & Howitt (2011). This study can be regarded as an extension of the framework introduced and used in these works, with new applications and with additional data, thereby specifically focussing on measuring and analysing productivity gains. The previously developed theoretical and methodological framework is therefore adapted to our specific objectives, i.e., implementing a fully flexible functional form, adapting the estimation routine to support additional data, constructing additional procedures to verify several productivity-related hypotheses, introduce an outlier removal procedure, etc. Throughout this work, we attempt to provide the reader with the most important aspects of these previous works, such that one can understand the basic principles of the framework. To avoid unnecessary paraphrasing, the interested reader is therefore referred to the concerned works for further details, if necessary.

1.2. Motivation

Farm productivity gains over time have generally been measured at the country or sectoral level, which will become apparent in our literature review in the section hereafter. In this work however, we estimate them at the individual farm level using microeconomic data. This allows us to reveal the heterogeneity in productivity gains across individual farms, to find possible explanatory factors attributing to this heterogeneity, such as input mix, output mix, farm size, and farm location, and to detect whether this heterogeneity in productivity gains across farms tends to converge or diverge during the last decades. In doing so, we go one step beyond by comparing farms with different characteristics, rather than comparing the performances of a particular sector or country as a whole. This enables us to identify precisely which subregions obtain certain degrees of productivity gains, or which farm characteristics are the most important determinants for achieving higher productivity gains. This kind of information can be of great importance for policy makers for instance. It also allows us to contribute to the current debate on whether a slowdown in farm productivity gains is occurring in the European Union, and suggest possible factors at play. Moreover, by adopting the microeconomic approach, we could, for instance, identify precisely those (types of) farms or regions that are falling behind and consequently redirect R&D institutes to focus on the development or improvement of technologies particularly suited for them, or review certain policy measures.

But why should we be interested in measuring these productivity gains? As will become apparent in section 2, productivity growth represents that part of production growth that is not explained by an increased use of inputs. This could, for instance, be due to technological progress, institutional adaptation, human capital development, improvement in physical infrastructure, changing government policies, etc. As mankind, our development throughout history has always depended upon achieving higher productivity levels, thereby enabling us to feed more people, maintain other dietary patterns and to attain higher levels of wealth and well-being in general. This, however, is not a story of the past, but remains acutely imperative, as we face enormous demographic challenges, ecological challenges and global climate changes today, for all of which further productivity gains are indispensable to overcome them. Boosting productivity levels is also a crucial requirement to increase the well-being of rural households (particularly for those in developing countries), as food could be offered at lower prices. By keeping prices low, poor consumers will be able to meet their needs, while farmers can still make positive profits as they become more productive and, hence, face lower costs. In such a way, productivity gains can increase overall welfare. Moreover, productivity gains improve the efficiency of our use of resources, bringing us one step closer to a sustainable world. Measuring and analysing these productivity gains is therefore important to asses our capacity for further development. It can also shed light on the impact of government policies and helps to assess the role of public research (e.g., the return on investment in public R&D). Finally, measuring productivity gains enables us to make a comparison of the within- and across country performances.

The structure of this work is as follows. Section two provides a concise review of the most important publications contributing to the study of technical change and total factor productivity (TFP). Thereby, we will introduce the general definitions of productivity and efficiency, their components, and how to measure them. Afterwards, we will discuss the results found in the most recent empirical literature on productivity analysis and examine how they have been obtained. Consequently, section three introduces the analytical framework according to which our study is conducted. First of all, this includes a general discussion of the cost function approach as a tool to assess productivity gains. Then, we will elaborate upon the specification of the particular cost function constructed for this analysis and its properties for it to be theoretically consistent and well-specified. The final part of section three will be dedicated to the actual productivity indicators, derived from the cost function estimation. Any occurrence of productivity gains will be represented by these indicators. We will also discuss several determinants underlying (some of) these indicators in an attempt to verify several 'common sense' hypotheses. Section four is an introduction to the empirical part of our work, including the presentation of the EU-FADN (and other) data, the way this data is prepared for the estimation process, and the general principles of the Stata routine we developed. This section also introduces the three regions that are analysed during the empirical part of this work, which are the three most important regions of for cereal production in the EU. Next, in section five, we start with specifying the exact principles according to which our empirical estimations are performed, the different conditions we impose or don't impose, and the way we deal with outliers. Consequently, we report and discuss the most relevant results for each of the three regions, and several indicators of goodness of fit to validate our model. During the final part of section five, we verify whether our *ex-ante* constructed hypotheses on the determinants underlying productivity gains hold or not. Finally, this work ends with a general discussion and some final remarks, followed by a reference list and the annexes.

2. Literature review

2.1. Basic introduction to productivity gains

In this section, we will summarize and discuss some theoretical background and the major results of several previous studies on technical change, multifactor productivity (MFP) and total factor productivity (TFP) in the agricultural sector. According to Ball, Bureau, Nehring & Somwaru (1997), a productivity index is generally defined as an output index divided by an input index, where output is defined as gross production leaving the farm as opposed to real value added and input includes labour, capital and intermediate inputs. Several functional forms can be used to construct these quantity indices (e.g., Laspeyres, Paasche, Fisher, Törnqvist…). Thus, TFP reflects output per unit of some combined set of inputs: an increase in TFP reflects a gain in output quantity which is not originating from an increase of input use. As a result, TFP reveals the joint effects of many factors including new technologies, economies of scale, education, managerial skill, and changes in the organization of production. Consequently, TFP growth is defined as the residual growth in outputs not explained by the growth in input use (Latruffe, 2010). Calculation of TFP requires a large amount of data, many of which are incomplete and/or require estimations and interpolations (European Commission, 2014).

Increased agricultural productivity is critical for meeting the challenge of feeding more than nine billion people by the middle of this century. Therefore, it is crucial to understand the measures of productivity growth and its causes in order to provide policy makers with the required insights for them to develop the adequate policies and right incentives to meet the challenges of a crowded world (Fuglie, Wang & Ball, 2012). Therefore, this review will commence by elaborating a theoretical background concerning the measurement of efficiency and productivity, followed by a discussion of some of the most important empirical studies concerning agricultural productivity.

2.2. Productivity and efficiency

2.2.1. General definition of productivity and efficiency

Latruffe (2010) gives an extended review of the literature on competitiveness, productivity and efficiency in the agricultural and agri-food sectors, thereby clarifying concepts and terminology often used in this area. The author states that productivity is one of the key determinants of a firm's competitiveness, which in turn determines a nation's social welfare, along with other factors, as depicted by Figure 1. The European Commission (2009) considers productivity even as the most reliable indicator for competitiveness over the long term.

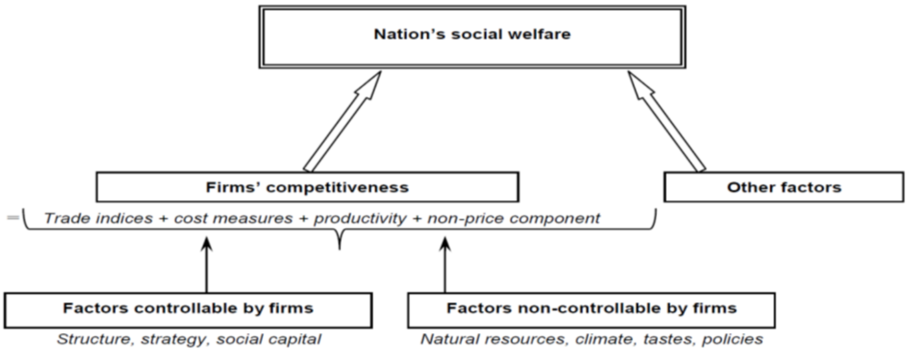

Figure 1. Measurement, determinants and effect of competitiveness.
Source: Latruffe (2010).

2.2.2. The components of productivity improvement

In what follows, some general concepts regarding productivity are explained according to Latruffe (2010). At first, potential productivity improvement is evaluated when firms are compared to a benchmark: in cross-section data, firms are compared with each other in the same period, while in a time-series approach one firm is considered during two periods. In the first case, a firm can increase its productivity in comparison with other firms by improving its efficiency and/or by reaching an optimal scale of operation. In the second case, all firms can increase their productivity owing to technological progress. This can be seen in Figure 2, which depicts a simple single-output, single-input case. The production function *f* relating the output produced, *y*, with the input used, *x*, indicates the maximum output produced for a given level of inputs (the production possibilities) and thus reflects the current state of technology in the industry. Productivity improvement can be of the three following kinds.

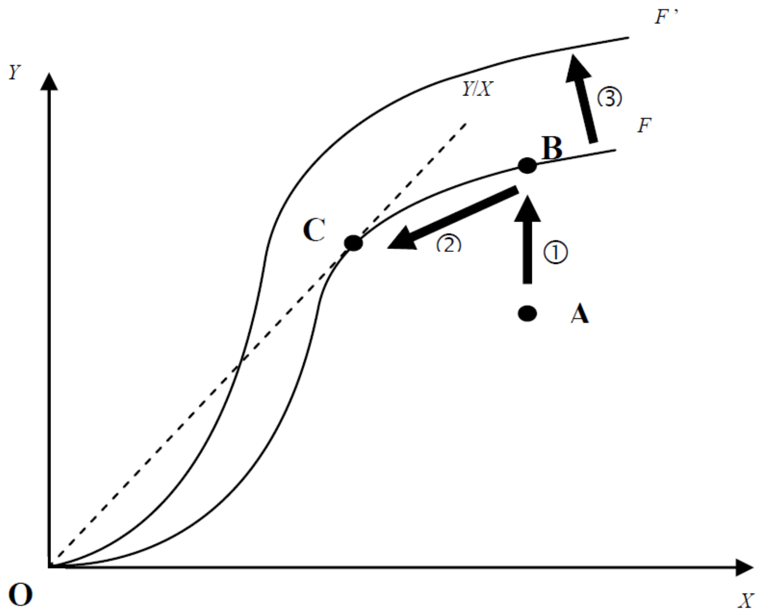

Figure 2. Three possible productivity improvements for firms.
Source: Latruffe (2010).

- Efficiency increase:

In comparison with other firms, productivity improvement can result from more efficient use of the existing technology. In Figure 2, firm *A*, for example, would be able to produce more output with the same input use, that is to say it could use its input in a more efficient way. This is depicted by a movement from *A* towards the frontier *f*, parallel to the *y*-axis (movement ①). The movement could also be parallel to the *x*-axis and would correspond to a decrease in input use while the same output is produced. Clearly, the closer a firm operates to the frontier, the more efficient it is. Efficiency is therefore a measure of the distance from a given observation to the frontier (see further). Firms operating on the frontier are said to be fully technically efficient in their use of inputs, e.g., firms *B* and *C*, and those operating beneath it are inefficient, e.g., firm *A*. This notion of efficiency refers to the neoclassical efficient allocation of resources and the Pareto optimality criterion. Considering a firm that uses several inputs and produces several outputs, this firm is efficient in the way it allocates its resources if a reduction in any input requires an increase in at least one other input or a reduction in at least one output (Lovell, 1993).

- Exploiting economies of scale:

A second productivity improvement for a firm when compared with other firms can be achieved by exploiting economies of scale. Potential economies of scale can be identified by the scale elasticity, calculated as the ratio of the proportionate increase in output to the proportionate increase in all inputs. At point *C* the elasticity of scale is one and therefore firm *C* has an optimal scale. Firm *B* by contrast has an elasticity of scale less than one and therefore exhibits diseconomies of scale, while a firm situated on the left of *C* would have a scale elasticity greater than one and hence exhibit economies of scale. Exploiting economies or diseconomies of scale is therefore a productivity improvement, characterised by a movement on the frontier *f* (movement ② for example).

- Technological progress:

The third possibility of productivity change refers to the long term and is called technological change. Technological progress, that is to say improvement in the state of technology, happens for example when a new and higher performing production or transformation process is available on the market. It results in an upward shift of the production frontier from *f* to *f* " (movement ③). This progress should be able to apply to all firms (assuming that they all have the same access to the new technology), and implies that they would be able to produce more using the same level of input. On the other hand, technological regress, for example due to a deterioration of worker qualifications, would imply a downward shift of *f* and therefore a decrease in the output produced per input used.

According to Coelli, Rao, O'Donnell & Battese (2005), the terms 'productivity' and 'efficiency' have frequently been used as synonyms. This is unfortunate, because they are not precisely the same thing. To illustrate the distinction between technical efficiency and productivity we utilise Figure 3, which is similar to Figure 2. In this figure, we use a ray through the origin to measure productivity at a particular data point. The slope of this ray is *y/x* and hence provides a measure of productivity. If the firm operating at point *A* were to move to the technically efficient point *B*, the slope of the ray would be greater, implying higher productivity at point *B.* However, by moving to point *C*, the ray from the origin is at a tangent to the production frontier *F'* and hence defines the point of maximum possible productivity. This latter movement is an example of exploiting scale economies, as discussed above. The point *C* is the point of (technically) optimal scale. Operation at any other point on the production frontier results in lower productivity. From this discussion, we conclude that a firm may be technically efficient but may still be able to improve its productivity by exploiting scale economies.

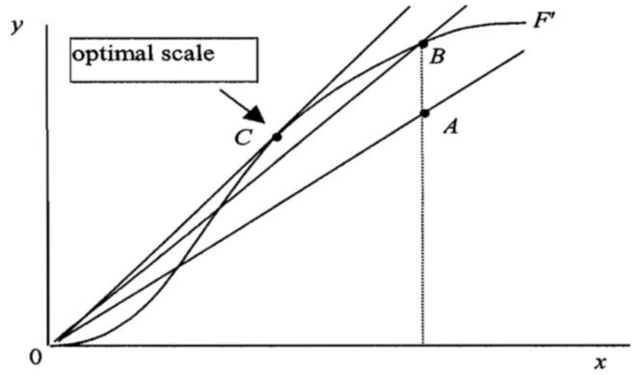

Figure 3. Productivity, technical efficiency and scale economies
Source: Coelli, et al. (2005).

2.2.3. Measurement of efficiency

2.2.3.1. Mathematical representation

According to Latruffe (2010), efficiency gives an indication of whether firms are able to use the existing technology in the best way possible. It has three components: scale efficiency, technical efficiency and allocative efficiency. *Scale efficiency* gives insights into whether the firm operates at an optimal or sub-optimal size. Firms that are scale efficient operate under constant returns to scale (CRS) and have a scale elasticity of one, while scale inefficient firms could exploit scale economies or diseconomies. *Technical efficiency* (sometimes referred to as pure technical efficiency, as opposed to scale efficiency) assumes variable returns to scale (VRS) and shows whether a firm is able to attain the maximum output from a given set of inputs. It refers to a physical notion, independent of input and output prices. By contrast, the *allocative efficiency* of a firm (also called its price efficiency) reflects its ability to use inputs in their optimal proportions given their respective prices, or to produce an optimal combination of outputs given their respective prices. A firm is allocatively efficient if its outputs and inputs maximise its profit (or minimise its costs) at given prices. Allocative efficiency implies technical efficiency, as in order to maximise its profits, the firm must firstly lie on the production frontier. However, technical efficiency does not necessarily imply allocative efficiency, since the combination of outputs and inputs can be optimal with respect to the production possibilities, but not be profit maximising. This can be seen in Figure 4 depicted below. Technical, scale and allocative efficiency scores multiplied by each other make up the overall efficiency of a firm, sometimes called its economic efficiency.

The mathematical description of technical and allocative efficiency was firstly formulated by Farrell (1957). The author described the efficiency in an input-orientation context, that is to say in terms of potential input reduction holding the output level unchanged (by contrast to the output-orientation case, which relates to a potential output increase while keeping the same level of input use). Figure 4, based on Farrell (1957), depicts the case of a firm producing one output y with two inputs, x_1 and x_2. The production frontier f characterises the isoquant describing the minimum possible combinations of the two inputs that firms can use for producing one unit of output. The frontier bounds the observations, in the sense that the observed firms lie on or beyond it, e.g., Q and P (while R is not a firm). f is the technical efficiency frontier: firms lying on the frontier have no possibility of reducing one input without increasing another input, and are therefore technically efficient.

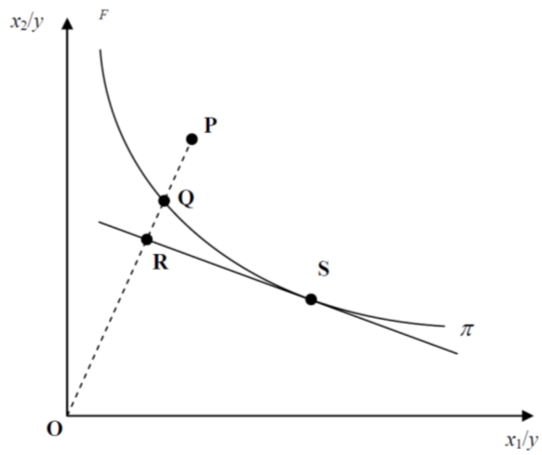

Figure 4. Input-orientated representation of technical and allocative efficiency of firms
Source: Farrel (1957).

Firm P is technically inefficient as it lies beyond the frontier. However, P and the technically efficient firm Q use the same proportion of inputs, as they both lie on the ray OP, which represents a constant ratio of the two inputs. P could therefore reduce both inputs by PQ and still produce the same level of output. The straight line π represents the input price ratio, which is the isocost, that is to say the least costly combination of inputs for producing one unit of output. Firm S is allocatively efficient as the slope of f equals the slope of π at S. However, firm Q, is technically but not allocatively efficient: it could reduce its input costs by QR and still produce the same level of output.

Measuring efficiency means measuring the potential input reduction, or potential output increase, relative to a reference. The major issue is therefore to define this reference, that is to say, to construct the efficient frontier. In practice, however, only inputs and their output realisations are observed. The production function that defines the frontier is unknown. Techniques for defining the frontier can be categorised as parametric and non-parametric methods.

2.2.3.2. Measurement using non-parametric methods

In the non-parametric approach, the efficiency frontier is empirically constructed piece-wise in the output-input space by enveloping all observations in the sample, based on Farrell's (1957) graphical decomposition. However, the space depiction becomes more complex in a multi-output, multi-input framework as an envelopment surface is required. The introduction of a method using mathematical programming allows the calculation of the distance in such complex cases. The most popular method is the Data Envelopment Analysis (DEA), which is discussed in Paragraph 2.2.4.3 (Latruffe, 2010).

Recently, Cesaroni & Giovannola (2015) introduced a new non-parametric approach called 'average-cost efficiency', which relaxes the assumptions of convexity, CRS and differentiability of the production frontier that are imposed by DEA. In fact, only free disposal [1]and VRS are required in this new approach. In their paper, they introduce a new definition of an optimal scale size based on the minimization of unit costs and the corresponding measure (i.e., average-cost efficiency) combines scale and allocative efficiency. This generalizes the measurement of scale economies in efficiency analysis, while providing a performance criterion which is stricter than both cost efficiency and scale efficiency measurement. For more details on this approach, we refer to the paper in question.

2.2.3.3. Measurement using parametric methods

While DEA, using linear programming, constructs the efficiency frontier with the best performing farms of the sample, parametric methods rely on specifying a production function and estimating its parameters with econometrics. In this study, we are mainly interested in the parametric approach that consists of estimating a dual cost function and relating this to productivity. This concept is explained more in detail in the rest of the paper.

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[1] The assumption of free disposal simply requires that if a given bundle of products can be produced with a given vector of inputs, then that same combination may be produced by any other vector that is greater than or equal to the previous one. In other words, extra amounts of inputs can be eliminated at no costs. The idea of free disposal is related to the monotonicity assumption of the input requirement set (Cesaroni, 2011; Baumgärtner, Faber & Schiller, 2006).

2.2.4. Measurement of productivity and technological change

2.2.4.1. General characteristics

Firstly, it is important to note that, according to the OECD (2001), technological change does not necessarily translate into MFP or TFP growth. Economic theory and empirical work have accorded great importance to the distinction between embodied and disembodied technology. Embodied technological changes are advances in the design and quality of new vintages of capital and intermediate products: machinery and equipment embody the fruits of research performed by the capital goods-producing industry, and other sectors obtain access to the outcome of this research through the purchase of new capital equipment or intermediate goods. Disembodied technical change, on the other hand, relates to the advances in science, to blueprints and formulae and to the diffusion of knowledge of how things are done, including better management and organizational change. The distinction is important because the diffusion of embodied technical change is dependent on market transactions: investment in the improved capital or intermediate good will be undertaken until its marginal contribution to revenue generation just equals its user cost, itself dependent on the market price of the capital good. The diffusion of disembodied technical change is not necessarily associated with market transactions: information may circulate freely and its use by one person does not normally restrict its use by another one. Therefore, it might be harder to observe and to include in a profound analysis.

2.2.4.2. The index number approach

2.2.4.2.1. Desirable properties of an index

As mentioned above, a general measure of productivity is given by TFP indices that compare an aggregate output index to an aggregate input index. Thus, measuring productivity changes requires measuring changes in the levels of outputs produced and the associated changes in inputs used. As a result, the main issue is how to aggregate together various outputs and various inputs. The index number approach proposes explicit methods for aggregation of quantities (and prices). Thus, several ways of aggregation lead to different TFP indices. In general, price weights are used in the construction. These account for the relative share of each output in the firm's revenue and for the relative share of each input in the firm's costs. Note already that each index implicitly assumes a specific underlying production function. For example, the Laspeyres index implies a Leontief production function, while the Törnqvist index is consistent with a translog function (Capalbo, Ball & Denny, 1990).

There are different desirable properties for an index, among which:

- *positivity:* the index (price or quantity) should be positive everywhere.
- *continuity:* the index is a continuous function of prices and quantities.
- *proportionality:* if all prices or quantities increase by the same proportion, then the index should increase by that same proportion. In other words, an important requirement for the TFP index is that is homogenous of degree +1 in output quantities and homogenous of degree -1 in input quantities.
- *commensurability:* or *dimensional invariance*, i.e., the index (price or quantity) must be independent of the units of measurement.

- *time-reversal test:* for two periods t and $t+1$, the index must satisfy $I_{t,t+1} = \frac{1}{I_{t+1,t}}$.

- *mean-value test:* the price or quantity index at the aggregate level must lie between the respective minimum and maximum changes at the commodity level.

- *circularity test:* often referred to as *transitivity*, i.e., for any three periods t, $t+1$ and $t+2$, this test requires that $I_{t,t+2} = I_{t,t+1} * I_{t+1,t+2}$. In other words, a direct comparison between period t and $t+2$ yields the same index as an indirect comparison through period $t+1$.

In the following paragraph, we will specify the most commonly used methods to aggregate input and output quantities in order to construct TFP indices. In Paragraph 2.2.4.3 we will discuss another concept for efficiency and productivity measurement, DEA, and hereby we will pay special attention to another useful TFP index: the Malmquist TFP index.

2.2.4.2.2. Commonly used indices

Laspeyres TFP index

Equation 1 describes how to obtain a Laspeyres quantity index. Consequently, the Laspeyres TFP index can be calculated by dividing the Laspeyres output quantity index by the Laspeyres input quantity index (Eq. 2). This concept also applies for other TFP indices. In these formulae, we calculate the quantity change indices for *N* goods, using the input/output price vector *p* and input/output quantity vector *q* from period *t* to $t+1$ (Coelli et al., 2005). The Laspeyres quantity index is exact for a fixed coefficient function (like a Leontief).

$$Q^L_{t,t+1} = \frac{\sum_{i=1}^{N} p_i^t q_i^{t+1}}{\sum_{i=1}^{N} p_i^t q_i^t} \tag{Eq. 1}$$

$$TFP_{t,t+1} = \frac{Output\ Index_{t,t+1}(Laspeyres)}{Input\ Index_{t,t+1}(Laspeyres)} \tag{Eq. 2}$$

Paasche TFP index

Similarly to the Laspeyres TFP index, the Paasche TFP index is calculated by dividing the corresponding output and input quantity indices, described by Equation 3. The Paasche index is exact for a linear function.

$$Q^P_{t,t+1} = \frac{\sum_{i=1}^{N} p_i^{t+1} q_i^{t+1}}{\sum_{i=1}^{N} p_i^{t+1} q_i^t} \tag{Eq. 3}$$

Törnqvist TFP index

A Törnqvist quantity index is defined as described by Equation 4 and its logarithmic form by Equation 5, in which $w_i^t = \frac{p_i^t q_i^t}{\sum_{i=1}^{N} p_i^t q_i^t}$ represents the revenue or cost share of the output or input respectively for good *i* at time *t*.

$$Q_{t,t+1}^{T} = \prod_{i=1}^{N}\left[\frac{q_i^{t+1}}{q_i^{t}}\right]^{\frac{w_i^t+w_i^{t+1}}{2}}$$

(Eq. 4)

$$\ln Q_{t,t+1}^{T} = \sum_{i=1}^{N}\left(\frac{w_i^t + w_i^{t+1}}{2}\right)(\ln q_i^{t+1} - \ln q_i^{t})$$

(Eq. 5)

The Törnqvist TFP index is consistent with a translog function and is generally defined in its logarithmic form as in Equation 6 (Capalbo, Ball & Denny, 1990; Coelli et al., 2005).

$$\ln(TFPC_{t,t+1}) = \frac{1}{2}\sum_{j=1}^{J}(r_j^t + r_j^{t+1})(\ln y_j^{t+1} - \ln y_j^{t}) - \frac{1}{2}\sum_{k=1}^{K}(s_k^t + s_k^{t+1})(\ln x_k^{t+1} - \ln x_k^{t}),$$

(Eq. 6)

where $TFPC_{t,t+1}$ is the change in TFP between periods *t* and $t+1$; y_j^t is the quantity of the *j*-th output in the *t*-th period, with *J* the number of different outputs; x_k^t is the quantity of the *k*-th input in the *t*-th period, with *K* the number of different inputs; $r_j^t = \frac{p_j^t y_j^t}{\sum_{j=1}^{J} p_j^t y_j^t}$ is the share of the *j*-th output in the total revenue in the *t*-th period, with p_j^t the *j*-th output price in the *t*-th period; $s_{kt} = \frac{w_k^t x_k^t}{\sum_{k=1}^{K} w_k^t x_k^t}$ is the share of the *k*-th input in the total cost in the *t*-th period, with w_k^t the *k*-th input price in the *t*-th period.

The Törnqvist index satisfy all the properties mentioned in Paragraph 2.2.4.2.1, except for the circularity (transitivity) property. As it is exact for a translog function, it is a second order flexible form and therefore referred to as a 'superlative' index.

Fisher TFP index

Diewert (1992) suggests the use of the Fisher index, which has many desirable properties and is therefore sometimes referred to as the 'Fisher Ideal Index'. The Fisher index is the geometric mean of the Laspeyres and Paasche index numbers as defined by Equation 7.

$$Q_{t,t+1}^{F} = \sqrt{Q_{t,t+1}^{L} Q_{t,t+1}^{P}} = \sqrt{\frac{\sum_{i=1}^{N} p_{i,t} q_{i,t+1}\ \sum_{i=1}^{N} p_{i,t+1} q_{i,t+1}}{\sum_{i=1}^{N} p_{i,t} q_{i,t}\ \sum_{i=1}^{N} p_{i,t+1} q_{i,t}}}$$

(Eq. 7)

In many respects, the Fisher index is more intuitive than the Törnqvist index and, more importantly, it decomposes the value index exactly into price and quantity components. The fact that it is in an additive format also makes the Fisher index more easily understood. The Fisher index is exact for a quadratic function, thus it is also referred to as a 'superlative' index. Since the Fisher and Törnqvist index numbers both provide reasonable approximations to the true output and input quantity, these indices are used in most practical applications involving time-series data and both formulae yield very similar numerical values for the TFP index

(Diewert, 1992). Also, similarly to the Törnqvist index, the Fisher index satisfies all the properties mentioned in Paragraph 2.2.4.2.1, except for the circularity (transitivity) property. This issue will be addressed in the next paragraph. Furthermore, the Fisher TFP index satisfies several additional properties (not mentioned here), including the useful ability to accommodate for zeros in the data (Coelli et al., 2005).

2.2.4.2.3. The Lowe approach

As will become apparent in Paragraph 2.3 on the empirical literature, most reported studies investigate productivity growth based on a common indicator: TFP. As mentioned above, this indicator is usually constructed using a Laspeyres, Paasche, Fisher or Törnqvist indices and is systematically adopted by most authors. However, in O'Donnell (2012), the author states that these well-known indices fail to satisfy a common-sense transitivity axiom (as discussed earlier). Remind that transitivity guarantees that a direct comparison of two observations (i.e., firms or periods) will yield the same estimate of TFP change as an indirect comparison through a third observation. The usual solution to the transitivity problem involves a geometric averaging procedure due to Elteto & Koves (1964) and Szulc (1964). Unfortunately, although they may be transitive, these so-called EKS indices fail an identity axiom. The identity axiom guarantees that if outputs and inputs are unchanged then the TFP index will take the value one (i.e., indicate that productivity is also unchanged). O'Donnell (2012) proposes a new TFP index (i.e., the Lowe TFP index) that satisfies both the transitivity axiom and the identity axiom. After estimating the Lowe TFP index, the article decomposes this index into measures of technical change and efficiency change.

Let y_{ft} ($\in R_+^N$) and x_{ft} ($\in R_+^M$) denote vectors of output and input quantities respectively, p_{ft} ($\in R_+^N$) and w_{ft} ($\in R_+^M$) denote vectors of output and input prices respectively, for firm *f* in period *t*. In O'Donnell (2008), TFP of the firm was defined by $TFP_{ft} = Y_{ft}/X_{ft}$, where $Y_{ft} \equiv Y(q_{ft})$ is an aggregate output and $X_{ft} \equiv Y(x_{ft})$ is an aggregate input. The only requirements placed on the aggregator functions $Y(.)$ And $X(.)$ are that they be nonnegative, nondecreasing, and linearly homogeneous. Now, the Lowe TFP index that compares firm *f* in period *t* with firm *h* in period *s* is given by Equation 8:

$$TFPI_{hsft} = \frac{TFP_{ft}}{TFP_{hs}} = \frac{YI_{hsft}}{XI_{hsft}} = \frac{p_0'\, y_{ft}}{p_0'\, y_{hs}} \frac{w_0'\, x_{hs}}{w_0'\, x_{ft}}, \tag{Eq. 8}$$

where $YI_{hsft} = Y_{ft}/Y_{hs}$and $XI_{hsft} = X_{ft}/X_{hs}$. Thus, within this framework, TFP growth is a measure of output growth divided by a measure of input growth, which is how productivity is usually defined. Associated with any non-zero aggregate quantities are implicit aggregate prices $P_{ft} = p_{ft}' y_{ft}/Y_{ft}$ and $W_{ft} = w_{ft}' x_{ft}/X_{ft}$. The existence of these implicit prices means that profit can be written as $\pi_{ft} = P_{ft}Y_{ft} - W_{ft}X_{ft}$ and profitability can be written as $PROF_{ft} = (P_{ft}Y_{ft})/(W_{ft}X_{ft})$. Furthermore, the paper shows that the index that compares the profitability of firm *f* in period *t* with the profitability of firm *h* in period *s* can be expressed by Equation 9:

$$PROFI_{hsft} = \frac{PROF_{ft}}{PROF_{hs}} = TTI_{hsft} * TFPI_{hsft}, \tag{Eq. 9}$$

with $TTI_{hsft} = PI_{hsft}/WI_{hsft}$, where $PI_{hsft} = P_{ft}/P_{hs}$ (an output price index) and $WI_{hsft} = W_{ft}/W_{hs}$ (an input price index). Thus, TTI_{hsft} is a terms of trade (TT) index measuring output price change relative to input price change. For more details on these indices, we refer to the paper of O'Donnell (2012). It is apparent from Eq. 9 that *i)* if the reference and comparison firms receive the same prices for their outputs and pay the same prices for their inputs, then the TT index will equal unity and any changes in profitability will be plausibly attributed entirely to changes in TFP; *ii)* if two firms use the same inputs to produce the same outputs, then any changes in profitability will be attributed entirely to changes in prices; and *iii)* if profitability is constant, then a TFP index can be computed as the reciprocal of a TT index.

The author illustrates the possibilities of this framework by estimating and decomposing the Lowe TFP index for the agricultural sector of the state of Alabama for the period 1960 – 2004. His results showed that during this period the estimated profitability in Alabama increased by 4.6% due to the combined effects of a 49.6% fall in the terms of trade and a 107.6% increase in TFP. In turn, estimated TFP increased due to an 81.4% increase in the maximum possible TFP (i.e., "technical change") and a 14.48% increase in overall efficiency. Finally, this estimated overall efficiency increased due to a 3.2% increase in output-oriented technical efficiency and a 10.9% increase in output-oriented scale-mix efficiency. When comparing different U.S. states, the Lowe TFP index indicates a considerable heterogeneity among states, as one state was 39% more productive than the other.

Furthermore, using the same framework, the average annual rate of TFP growth in U.S. agriculture is estimated to have been 2.23% in the 1960s, 0.56% in the 1970s, 3.06% in the 1980s, and 1.01% from 1990 to 2002. These estimated rates of growth are generally quite different from the Alston, Andersen, James & Pardey (2010) and Ball et al. (1997) estimates, discussed in Paragraph 2.3. The main driver of TFP change over the sample period has been technical progress (i.e., at an annual average rate of 1.84% in the 1960s and 2.30% in the 1990s). These non-parametric estimates are similar to parametric estimates reported elsewhere in the literature [e.g., 1.8% reported by Ray (1982)]. The author also finds that levels of technical efficiency have been stable and high. These results support the view that R&D expenditure has led to expansions in the production possibilities set, that U.S. farmers adopt new technologies quickly and make relatively few mistakes in the production process, and that they rationally adjust the scale and scope of their operations in response to changes in prices and other production incentives

2.2.4.3. The data envelopment approach

As already mentioned, another well-known concept for measuring efficiency and productivity is DEA. Introduced by Charnes, Cooper & Rhodes (1978), the underlying concept is to use linear programming to construct the efficiency frontier with the best performing firms among the observations. Inefficient firms are projected on the frontier along a ray of constant input ratio and the distance to their projection gives their efficiency score. Calculating technical efficiency with DEA allows a decomposition of technical efficiency (then called total technical efficiency) into pure technical efficiency and scale efficiency. Total technical efficiency is measured under the assumption of CRS and represents the technical efficiency in a long-term optimum, that is to say when the firm has an optimal scale of operation. The pure technical efficiency component is calculated under the VRS assumption and relates purely to management practices. It is a result of the operator's management behaviour rather than the firm's operating scale. Scale efficiency is the residual between the measure under CRS and the measure under VRS.

According to Coelli et al. (2005), this non-stochastic non-parametric method, DEA, is used for identifying production frontiers and for computing input and output distance functions. Distance functions are very useful in describing the technology in a way that makes it possible to measure efficiency and productivity and allow one to describe a multi-input, multi-output production technology without the need to specify a behavioural objective (such as cost-minimisation or profit-maximisation). An input distance functions characterises the production technology by looking at a minimal proportional contraction of the input vector, given an output vector. An output distance function on the other hand, considers a maximal proportional expansion of the output vector, given an input vector. Figure 5 illustrates the concepts of output distance functions and input distance functions using the production possibility frontier (PPF), *PPC-p(x)*, or the isoquant, *Isoq-L(q)*, for two outputs, q_1 and q_2, or two inputs, x_1 and x_2, respectively. The value of the distance function for the point, *A*, is equal to the ratio $\partial = 0A/0B$.

Distance functions

OUTPUT DISTANCE FUNCTION	**INPUT DISTANCE FUNCTION**

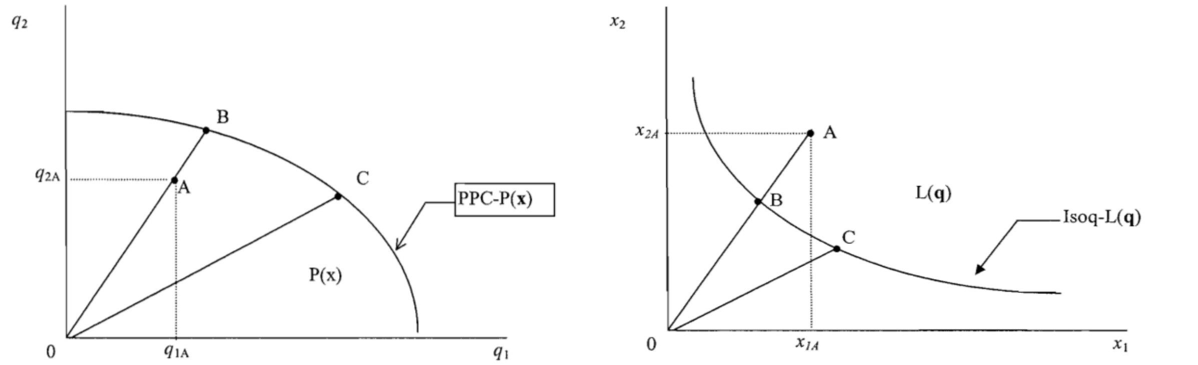

Figure 5. Concepts of output distance function (L) and input distance function (R). The value of the distance function for point *A* is equal to the ratio $\partial = 0A/0B$.
Source: Coelli, et al. (2005).

As previously mentioned, productivity (and efficiency) measurement is an important research topic of DEA (Wang & Lan, 2011). A very useful approach for productivity measurement in DEA is the Malmquist TFP index, which was named after Professor Sten Malmquist, on whose ideas the Malmquist TFP index is based. This index was introduced by Caves, Christensen & Diewert (1982). The index number approach, which we already discussed above, assumes that firms are efficient and therefore the TFP indices mentioned in Paragraph 2.2.4.2.2 measure only the technological change. In contrast, Malmquist indices provide a decomposition of the productivity change into efficiency change and technological change. In addition, data about prices and quantities as well as assumptions concerning the behaviour of producers (e.g., cost minimization or profit maximization) and the structure of technology are not necessary (Latruffe, 2010; Rungsuriyawiboon & Lissitsa, 2017). Therefore, the Malmquist TFP index has been extensively applied in the literature to investigate TFP growth. The Malmquist indices, as introduced by Caves et al. (1982), and their decomposition into efficiency change and technological change was proposed by Nishimizu & Page (1982) and Färe, Grosskopf, Lindgren

& Roos (1992). The Malmquist index of productivity change between periods t and $t+1$, $MQ_{t,t+1}$, is defined by Equation 10.

$$MQ_{t,t+1} = \left[\frac{D^t(x_{t+1}, y_{t+1})}{D^t(x_t, y_t)} \frac{D^{t+1}(x_{t+1}, y_{t+1})}{D^{t+1}(x_{t,} y_t)}\right]^{\frac{1}{2}}$$

(Eq. 10)

Where $D^t(x_{t+1}, y_{t+1})$ is the distance from observations in the $t+1$ period to the frontier of the t-th period; $(x_{t,} y_t)$ is the input-output vector in the t-th period. As mentioned, the Malmquist TFP indices can further be decomposed into technological change and technical change, itself being decomposed into pure technical efficiency change and scale efficiency change. These decompositions can be found in Annex 1. All computed indices (Malmquist TFP, total technical efficiency, pure technical efficiency, scale efficiency, technological change) are compared to 1. An index equal to 1 indicates no change over the period considered. An index greater than 1 indicates progress, with the difference with 1 giving the percentage progress, while an index less than 1 indicates deterioration, with the difference with 1 giving the percentage deterioration (Latruffe, 2010).

It must be noted that, within this framework, efficiency estimates are likely to be biased towards higher scores. This bias arises when the most efficient firms within the population are not contained in the sample at hand. As a consequence, inefficient firms form the envelopment frontier. The efficiency degree of all other firms is then measured relative to the sample frontier instead of the true population frontier, and therefore might be biased. Possible solutions like 'bootstrapping techniques' are proposed to remedy the sampling problem, but this is beyond the scope of this review (Latruffe, 2010).

Malmquist indices can be calculated by parametric and non-parametric methods. As an illustration of this concept, we discuss a study made by Rungsuriyawiboon & Lissitsa (2017), that measures TFP growth in the European agriculture using Malmquist indices based on the non-parametric technique of data envelopment to fit distance functions index for 44 countries based on quantity data on 127 agricultural commodities. This study also examines the levels and trends in agricultural productivity of transition countries and compare their agricultural productivity with the EU countries for the period 1992 – 2002. The transition countries are the Central and Eastern European Countries (CEEC) and the Newly Independent States (NIS) after the breakdown of the former Soviet Union. The authors restrict the decomposition of the Malmquist TFP index into an 'efficiency change' component and a 'technical change' component as sources attributing to the TFP growth, as described by Equation 11.

$$MQ_{t,t+1} = \frac{D^{t+1}(x_{t+1}, y_{t+1})}{D^t(x_t, y_t)} \left[\frac{D^t(x_{t+1}, y_{t+1})}{D^{t+1}(x_{t+1}, y_{t+1})} \frac{D^t(x_t, y_t)}{D^{t+1}(x_t, y_t)}\right]^{\frac{1}{2}}$$

(Eq. 11)

The first ratio outside the square brackets is called the 'efficiency change' component, which measures the change in the output-orientated measure of Farrell technical efficiency between periods t and $t+1$. The efficiency change component simply compares the distances of two observations, (x_t, y_t) and (x_{t+1}, y_{t+1}), to the corresponding production frontiers S^t and S^{t+1}.

It measures whether production is catching up with or falling behind the production frontier. It is assumed that this component captures diffusion of technology related to differences in knowledge and institutional setting. The remaining part of the index in Equation 11 is a measure of ‘technical change’. It is the geometric mean of the shift in technology in time t and $t+1$ at input levels x_t and x_{t+1}. This term captures changes in technology at a national level. Figure 6 illustrates how to define the output distances, which are component of the Malmquist TFP index decomposition. Consider the time period t and $t+1$, the observed input-output combination is located inside the production frontier which implies the productions are not technically efficient for both periods t and $t+1$. The output distance for the observation at time t, relative to the production frontier S^t, $D^t(x_t, y_t)$, is given by the ratio $\left(\overline{0b}/\overline{0a}\right)^{-1}$, while the output distance for the observation at time $t+1$, relative to the production frontier S^{t+1}, $D^{t+1}(x_{t+1}, y_{t+1})$, is given by the ratio $\left(\overline{0d}/\overline{0c}\right)^{-1}$. Values of these two output distances with respect to the same points in time are less than one. Figure 6 also presents how other required output distances with respect to two different points in time are defined. These output distances are also component of the Malmquist TFP index. The output distance $D^t(x_{t+1}, y_{t+1})$, which measures the proportional change in outputs required to make (x_{t+1}, y_{t+1}) feasible relative to the available production frontier S^t, is given by the ratio $\left(\overline{0e}/\overline{0f}\right)^{-1}$. Similarly, the output distance $D^{t+1}(x_t, y_t)$, which measures the proportional change in outputs required to make (x_t, y_t) feasible relative to the available production frontier S^{t+1}, is given by the ratio $\left(\overline{0f}/\overline{0a}\right)^{-1}$. Values of these two output distances with respect to the different points in time are greater than one. This framework, as applied in Rungsuriyawiboon & Lissitsa (2017), assumes a constant return to scale on the frontier technology. The main empirical results of this study will be discussed in Paragraph 2.3.2.

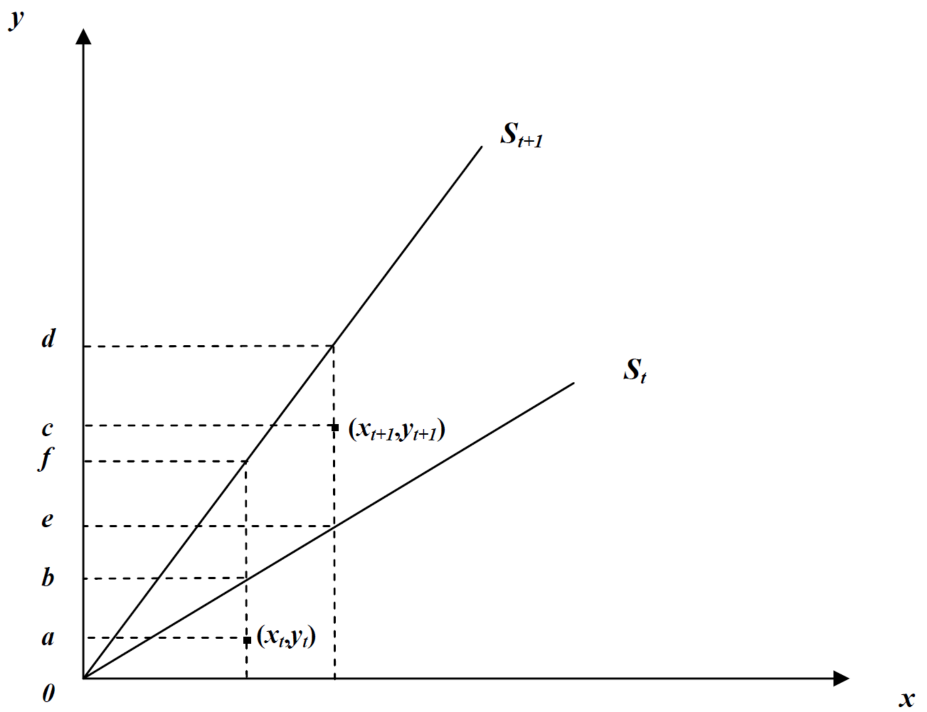

Figure 6. The output-orientated Malmquist TFP index decomposition under a constant return to scale production frontier
Source: Rungsuriyawiboon & Lissitsa (2017).

2.2.4.4. The cost function approach

2.2.4.4.1. Motivation for using cost functions

In this review, we will pay special attention to the cost function approach, because in what follows, we will perform a microeconomic analysis of the productivity gains of EU farms by estimating a multi-input, multi-output cost function. Therefore, other approaches, such as the profit function approach, will not be elaborately discussed here. The estimation performed by a cost function approach allows to derive total, average and marginal cost functions for individual farm output categories as well as input demand functions for individual farm input categories. This will result in useful information regarding current technology and concerning policy analysis, which is seldom directly available from data bases such as the EU-FADN. Furthermore, it will allow the calculation of marginal cost – output price ratios and technological and economic indicators such as cost flexibility and economies of scale, scope and size. Finally, it allows to measure the effects of technological change on input use and total cost. We also note it makes more sense to use the approach of cost minimization rather than profit maximization when studying historical farm behaviour in the EU, which has been strongly influenced by the common agricultural policy (CAP). For instance, implementing a quota system into a profit maximization framework would be very challenging, whereas it would impose few limitations in a cost minimization approach.

2.2.4.4.2. Properties of a cost function

Up until now, we have been mainly concerned with the physical relationships between inputs and outputs. In this section we look at how firms decide on the mix of inputs they wish to use (Coelli et al., 2005). Productivity and growth-accounting measures as described above have been discussed with the help of production functions and quantity measures of inputs and outputs. There exists an equivalent, and intuitively appealing "dual" approach to express advances in productivity as shifts of a cost function. A cost function shows the minimum input cost of producing a certain level of output, given a set of input prices. Chambers (1988) defines the cost function as described by Equation 12.

$$c(w, y) = \ min_{x \geq 0}\{w * x : x \in V(y)\} \tag{Eq. 12}$$

where w is a vector of strictly positive input prices, $V(y)$ represents the input requirement set and $w * x$ is the inner product $(\sum_{i=1}^{N} w_i x_i)$. This representation assumes that input prices are exogenous to the producer. Moreover, $c(w, y)$ depends on the technology since the only constraint to the minimisation problem in Equation 12 is that x be capable of producing at least output y. Note that the more a priori restrictions that are placed on the technology, the more constrained producers will be in solving the minimum-cost problem. This is perhaps best illustrated by the fact that without at least some assumptions on $V(y)$, the cost function will not even be well defined. Thus, the goal is to place as few restrictions as possible on the a priori behaviour of economic agents so as to permit the derivation of as general a behavioural response pattern as possible.

Irrespective of the properties of the production technology, the cost function satisfies the following properties (Coelli et al., 2005; Chambers, 1988):

- C.1 Nonnegativity: Costs can never be negative.

- C.2 Nondecreasing in w: An increase in input prices will not decrease costs. More formally, if $w^0 \geq w^1$, then $c(w^0, y) \geq c(w^1, y)$

- C.3 Nondecreasing in y: It costs more to produce more output. That is, if $y^0 \geq y^1$, then $c(w, y^0) \geq c(w, y^1)$

- C.4 Homogeneity (of degree +1): Multiplying all input prices by an amount $k > 0$ will cause a k-fold increase in costs (e.g., doubling all input prices will double cost). Mathematically: $c(k \cdot w, y) = k \cdot c(w, y)$, for $k > 0$.

- C.5 Concave and continuous in w: $c(\theta \cdot w^0 + (1-\theta) \cdot w^1, y) \geq \theta \cdot c(w^0, y) + (1-\theta) \cdot c(w^1, y)$, for all $0 \leq \theta \leq 1$. This statement is not very intuitive. However, an important implication of the property is that input demand functions cannot slope upwards.

- C.6 No fixed costs: It is costless to produce zero output. $c(w, 0) = 0$

Under relatively weak regularity conditions, cost functions can be derived from production functions, and vice versa, i.e., there is duality. To illustrate this point, one expresses a simple cost function *C* as $C = B \cdot Q \cdot c(w_1, w_2, \ldots, w_N)$, where *C* is total cost that varies as a function of the level of output, *Q*, of unit costs *c* (themselves dependent on input prices w_i) and of a parameter *B*. This parameter plays a role similar to the productivity parameter *A* in the production function $Q = A \cdot F(X_1, X_2, \ldots, X_N)$. It can indeed be shown that $\frac{d \ln A}{dt} = -\frac{d \ln B}{dt}$ (Chambers, 1988). Thus, the TFP productivity residual can be measured either as the residual growth rate of output not explained by the growth rate of inputs or as the residual growth rate of average costs not explained by change in input prices (OECD, 2001):

$$\frac{d \ln C}{dt} - \frac{d \ln Q}{dt} = \sum_{i=1}^{N} s_i \frac{d \ln w_i}{dt} - \frac{d \ln A}{dt}$$

(Eq. 13)

This equation states that the rate of growth of average costs equals the rate of growth of aggregate input prices, reduced by advances in TFP. A slightly different formulation is that productivity growth equals the diminution in total costs that is neither explained by a fall in output nor by substitution of inputs that have become relatively more expensive for those whose relative price has fallen. This formulation of TFP in terms of average costs lends a richer interpretation to technological change. It is intuitively plausible that total and average costs can be reduced by many means including technological innovations in an engineering sense but also by organisational innovations, learning-by-doing, and managerial efforts. The cost approach also shows how average cost can decline as a consequence of embodied technological change only: suppose that one of the inputs (e.g. computer services) exhibits falling prices (user costs) relative to other inputs as a consequence of (embodied) technical change. Most likely, a substitution process will take place where computer services replace other factors of production. The ensuing decrease in aggregate input prices leads to a fall in average costs, even if disembodied technology does not grow at all ($\frac{d\ln A}{dt} = 0$). Finally, the above formulation points to another representation and measurement of disembodied technical change; namely, the difference between the growth rate of output prices and that of input prices. In a competitive market, prices evolve in line with marginal cost. Further, under constant returns to scale, average costs of production equal marginal costs and consequently, the rate of change of average costs of production equals the rate of change of the market price of output, or the expression on the left-hand side of Equation 13. At the same time, the share-weighted average of the price changes of all inputs is an input price index, and its rate of change appears as the first expression on the right-hand side of Equation 13. It is then easy to see that the rate of disembodied technical change is the difference between the rate of change of the input price index and the output price index:

$$\frac{d\ln A}{dt} = \frac{d\ln P_I}{dt} - \frac{d\ln P}{dt},$$

where $\frac{d\ln P_I}{dt} \equiv \sum_{i=1}^{N} s_i \frac{d\ln w_i}{dt}$; $\frac{d\ln P}{dt} = \frac{d\ln C}{dt} - \frac{d\ln Q}{dt}$.

Furthermore, by the Shephard duality theorem, one shows that the input demand functions are the derivatives of the cost function with respect to the input prices (Sadoulet & de Janvry, 1995):

$$x_i = \frac{\partial c}{\partial w_i}$$

In other words, the Shephard's lemma states that, if the cost function is differentiable in input prices, then there exists a unique vector of cost-minimizing input demands that is equal to the gradient of the cost function in input prices.

Another important characteristic we would like to introduce is the potential existence of (quasi-)fixed inputs. Until now we have assumed that all inputs are variable, as they would be in the long run. For this reason, the cost function *c*(w, y) is sometimes known as a *variable* or *long-run cost function*. A useful variant of this function is obtained by assuming that a subset of inputs is fixed, as some inputs would be in the short run (e.g.: buildings, family labour in agricultural households). The resulting cost function is known as a *restricted* or *short-run cost function* (Coelli et al., 2005). Let the input vector *x* be partitioned as $x = (x_f, x_v)$, where x_f and x_v are subvectors containing fixed and variable inputs respectively, and let the input price vector *w* be similarly partitioned as $w = (w_f, w_v)$. Then the short-run cost minimisation problem can be written as:

$$c(w, y, x_f) = min_{x_v}\, w_v' x_v + w_f' x_f$$

Note that this problem only involves searching over values of the *variable* inputs. In every other respect, it is identical to the long-run cost minimisation problem of Equation 12. Thus, it is not surprising that $c(w, y, x_f)$ satisfies properties C.1 to C.5 (although the nonnegativity property can be strengthened – the short-run function is *strictly positive* owing to the existence of fixed input costs). In addition, $c(w, y, x_f) \geq c(w, q)$ (i.e., short-run costs are no less than long-run costs), and if $x_f^0 \geq x_f^1$, then $c(w, y, x_f^0) \geq c(w, y, x_f^1)$ (i.e., the function is nondecreasing in fixed inputs).

Another important characteristic we would like to stress is the *separability* of cost functions, as they can be weakly or strongly separable. Separability, in the framework of cost functions, permits one to construct composite prices using subvectors of input prices. This, in turn, permits further analysis of the cost function solely in terms of these composite prices. There are two kinds of separability: weak and strong separability. Weak separability of the cost function in terms of composite input prices requires by Shephard's lemma that the derived-demand elasticities for all individual inputs belonging to the same composite input with respect to a price of an individual input belonging to a separate composite input are equal. An alternative way to interpret the structure of a weakly separable cost function is a two-stage cost minimization process, analogue to a weakly separable production process according to a two-stage production process. Thus, each aggregate input is constructed in a cost-minimising fashion. This means that in the first stage of this process, individual inputs of their respective composite input are combined in a cost-minimising fashion to produce a single unit of every respective composite input. In the subsequent stages, these composite inputs are combined in a cost-minimising fashion to produce the final outputs. In other words, in the first stage, separate unit sub-cost functions are estimated for the composite inputs using the prices of the individual inputs in the respective composite inputs. In the subsequent stage, these unit sub-cost functions are interpreted as composite input prices and used as the basis of estimating a cost function dependent on output quantities and the composite input prices. An even stricter form is strong separability, which implies that the ratio of optimal derived demands from any two groups only depends on the prices in those two groups and output. This means that strong separability of the cost function implies weak separability, but not vice versa. This concept of separability can be very interesting from a theoretical and an empirical point of view. From an empirical perspective, the existence of a two-stage cost minimisation process suggests one way of attacking empirical estimation of a cost function that depends on too many input prices to be handled efficiently for a given data set. That is, in the first stage, separate cost functions are estimated for the aggregate inputs using the prices of the inputs in the respective subgroups. In the second stage, these sectoral cost functions are interpreted as aggregate input prices and are used as the basis of estimating a cost function dependent on *y* and the aggregate input prices (Chambers, 1988).

A final important and desired property is the *flexibility* of the cost function. A flexible form is capable of providing a second-order approximation to the behaviour of any theoretical plausible input demand system at a point in the input price-output space. More precisely, a flexible form can mimic not only the input quantities demanded, the output derivatives and the own-price elasticities, but also the cross-price elasticities, at a particular point. For more details concerning flexibility, we refer to Chambers (1988). These properties and some practical notions will be further elaborated in Paragraph 3.3. Both the theoretical concepts of separability and flexibility have been extensively discussed throughout the literature (e.g., Chambers, 1988; Sato, 1967; Diewert & Wales, 1995, etc.), however, this is beyond the scope of this work.

2.2.4.4.3. Commonly used cost functional forms

When using the cost function approach, it is important for one to know the implications of choosing a specific functional form, as a certain cost functional form is associated with a specific technology and will therefore impact one's results. Obviously, it is desirable for researchers to choose a functional form that satisfies all the desirable characteristics of a cost function (i.e., homogeneity, concavity, separability, flexibility, parsimony…), that is as general as possible and at the same time coincides with the reality. The most commonly used functional forms are represented in Table 1 (Sadoulet & de Janvry, 1995; Diewert, 1971).

Table 1. Most commonly used cost functional forms

The linear cost function	
$\boldsymbol{c(w,q) = q\sum_i \alpha_i w_i}$	associated with a Leontief production function
The Cobb-Douglas cost function	
$\boldsymbol{c(w,q) = A(q)\prod_i w_i^{\alpha_i}}$	associated with a Cobb-Douglas production function
The CES* cost function	
$\boldsymbol{c(w,q) = A(q)(\sum_i \beta_i w_i^{-\rho})^{-1/\rho}}$	associated to a CES production function (with an elasticity of substitution equal to the inverse of the elasticity of substitution in the cost function)
The translog cost function	
$\boldsymbol{\ln c(w,z,q) = \alpha + \sum_i \beta_i \ln x_i + \sum_i \sum_j \beta_{ij} \ln x_i \ln x_j}$	where *x* represents either an input price w_i, the output level q, or a fixed input z_m
The generalised Leontief cost function	
$\boldsymbol{c(w,q) = q\sum_i \sum_j b_{ij}\sqrt{w_i w_j}}$	with $b_{ij} = b_{ji}$ (symmetry), associated with a Leontief production function

* CES: constant elasticity of substitution

Sources: Sadoulet & de Janvry (1995); Diewert (1971).

Thus, in specifying functional forms for applied production analysis, it is advantageous to have estimable relationships that place relatively few prior restrictions on the technology. To some extent, the last sentence is self-contradictory since specifying an estimable form that does not restrict the technology is usually difficult (if possible). Estimability typically implies a choice of form, and once the form is parameterized in accordance with received economic theory (homogeneity, convexity, etc.), duality guarantees the existence of a unique dual function. As a simple example, suppose that the underlying production function, $f(x)$, is Cobb-Douglas. If an investigator utilizes a cost function linear in input prices, the applicability of the results is severely limited because such a cost structure presumes the existence of a Leontief and not a Cobb-Douglas technology (Chambers, 1988).

2.2.4.4.4. Indicators of cost and technical change

By performing a microeconomic analysis using the cost function approach, several additional indicators can be distinguished (Chambers, 1988). These indicators will be frequently used in the rest of this work. The first we would like to mention is the *rate of marginal cost diminution*, or RMCD, which is defined by Equation 14. If this rate is positive, the marginal costs (MC) diminish over time.

$$RMCD = -\frac{\partial MC_m}{\partial t} MC_m^{-1}$$

(Eq. 14)

A second indicator is the *rate of cost diminution*, *RCD* or $\theta(w, y, t)$, which is defined by Equation 15. If the RCD is positive, the change is progressive, i.e., total costs (TC) diminish over time.

$$RCD = \theta(w, y, t) = -\frac{\partial TC}{\partial t} TC^{-1}$$

(Eq. 15)

Another indicator is the *rate of technical change*, *RTC* or $\tau(x_1, \dots, x_I, t)$, defined by Equation 16, where $f(x_1, \dots, x_I, t)$ denotes the time-varying single-output production function.

$$RTC = \tau(x_1, \dots, x_I, t) = \frac{\partial \ln f(x_1, \dots, x_I, t)}{\partial t}$$

(Eq. 16)

If τ is positive, production increases over time, while holding inputs constant. Furthermore, it can be shown that

$$\tau(x_1, \dots, x_I, t) = \varepsilon^*(w, y, t) \cdot \theta(w, y, t)$$

where $\varepsilon^*(w_1, \dots, w_I, y, t)$ denotes the elasticity of size of the cost function associated with $f(x_1, \dots, x_I, t)$. The elasticity of size is the reciprocal of the cost flexibility $\eta = \frac{\partial\, TC}{\partial\, y}\frac{y}{TC}$. Now, for a multi-output firm, we derive that

$$\eta = \frac{\partial TC}{\partial y}\frac{y}{TC} = \frac{y}{TC}\sum_{m=1}^{M}\frac{\partial TC}{\partial y}\frac{\partial y}{\partial y_m} = \frac{y}{TC}\sum_{m=1}^{M}\frac{\partial TC}{\partial y_m} = \frac{y}{TC}\sum_{m=1}^{M} MC_m$$

using the identity $y = y_1 + \cdots + y_M$, which holds if all outputs are expressed in values. The elasticity of size for a multi-output firm is thus given by Equation 17 and can be used as such for computing the rate of technical change (i.e., the product of the elasticity of size and the rate of cost diminution).

$$\varepsilon^*(w_1, \dots, w_I, y_1, \dots, y_M, t) = TC\left(y\sum_{m=1}^{M} MC_m\right)^{-1}$$

(Eq. 17)

A final indicator we would like to mention is the *factor-biased technical change*, or *FBTC*, as defined by Equation 18. If the value of this indicator is negative, the technical change is input *i* saving.

$$FBTC = \frac{\partial \ln x_i\,(w_1, \ldots, w_I, y_1, \ldots, y_M, t)}{\partial t}$$

(Eq. 18)

2.3. Empirical literature

2.3.1. Introduction to empiric productivity research

During the making of this review, it has become apparent that productivity estimates can differ strongly and that many authors have different opinions on whether there has been a slowdown in agricultural productivity growth during the last centuries. The following section tries to bring some insights on the findings of some of the previous studies addressing this paramount debate. It is important to note that the goal of several of these studies is to calculate the returns of agricultural research and development (R&D). Therefore, they need to obtain and analyse data on the levels of productivity during a certain period and relate it to the expenses made on R&D during this period (while including certain lag-periods). In this paper, we will mainly focus on the data and results regarding productivity they obtained for their research.

But first, we would like to mention an important issue addressed in a recent study of Alston (2018). The author states that, since the introduction of the idea of the productivity "residual" to agricultural economics by Schultz (1956), much progress has been made in the decades since. Still, critical issues remain unresolved. This matters because agricultural innovation and productivity matter, and so do the related policies that rest to some extent on our established understanding of the economic relationships. In his paper, the author reviews some unsettled issues related to economic models and measures applied to agricultural R&D and productivity, and some unfinished business in terms of economic and policy questions that are not yet well answered. For instance, he demonstrates how two different datasets can yield very contrasting estimates, by estimating a Translog cost function model using the national annual data from the International Science and Technology Practice and Policy (InSTePP) Center on the one hand, and the U.S. Department of Agriculture (USDA) on the other hand, for the period 1949 – 2007. The two datasets imply quite different estimates for, amongst others, the rates of factor-neutral technical change (twice as fast using the InSTePP data compared with the USDA data), and some substantive differences in the detail of the pattern of factor-biased technical change (though both indicate that technical change has been land-, labour-, and capital-saving, and "other inputs"-using, consistent with the gross trends in factor shares).

2.3.2. Productivity of the U.S. agriculture

This section is dedicated to some studies conducted regarding U.S. agriculture in particular. The first group of reports we want to discuss here is based on the work done by Alston et al. (2010). In their book, they gather data to construct an index of productivity growth for the U.S. agriculture in order to calculate the returns on public agricultural R&D investments in a two-step procedure. Therefore, the authors make use of an uncommonly rich and detailed panel of U.S. state-level data, developed for this purpose. They also use these data and results for other publications, i.e. Alston (2010) and Alston, Andersen, James & Pardey (2011), which will be discussed later. The following paragraphs summarize their main results of their book. Firstly, the authors estimate that output from agriculture increased on average by 1.68% per year over the period 1949 - 2002, while inputs used by agriculture declined by 0.11% per year. So, measured MFP, as Fisher ideal discrete approximations of Divisia indices, grew by 1.78% per year. It thereby more than doubled from 100 in 1949 to about 257 in 2002. These approximations reflect a careful effort to account for variation over time and among states in the composition of the aggregates of inputs and outputs and thereby minimize the role of index number problems. It has to be noted that there is considerable heterogeneity among the different states.

Of the actual output in 2002, only 39% (i.e., $100/_{257} = 0.39$) could be accounted for by conventional inputs using 1949 technology, holding productivity constant. The remaining 61% is accounted for by economies of scale along with improvements in infrastructure and inputs and other technological changes. Hence, of the total production value, worth $173.3 billion in 2002, only 39%, or $67.3 billion, could be accounted for by conventional inputs using 1949 technology, and the remaining $106.0 billion is attributable to the factors that gave rise to improved productivity. In his latest paper (Alston, 2018) with additional data, the author introduces another way to grasp the remarkable productivity performance and the transformation in the U.S. agriculture in terms of the quantities of inputs that would be required to produce the 2007 quantity of output (2.7 times the 1949 output) using 1949 technology (i.e., productivity and factor shares): that is, 2.7 times the 1949 quantities. An increase to 2.7 times the actual quantities of land and labour (along with capital and other inputs) used in 1949 would require adding 2.0 billion acres (an area the size of the contiguous United States or Australia, much more than the total agricultural area in either country) to the 1949 quantity of land used in agriculture, and an additional 34 billion hours of operator, family, and hired labour (or about 12 million full-time equivalents); the required increase would be closer to 2.5 billion acres over the 2007 quantity of land and a fivefold increase over the 2007 farm labour force! Among the contributing factors is new technology, developed and adopted as a result of agricultural research and extension. Finally, they state that among the 48 states, the share of the total value of agricultural output in 2002 attributable to growth in productivity since 1949 averaged 58%.

Alston (2010) contains a review of the literature on the role of agricultural research and development in fostering innovation and productivity in agriculture. Of all the studies they reviewed, one clear message became apparent, namely that the rate of return of agricultural R&D is generally (very) large, implying marginal and average benefit-cost ratios much greater than 1.0. An implication of finding a marginal benefit-cost ratio greater than 1.0 is that it would have been profitable to have invested more, thereby possibly increasing productivity even more.

However, being very sceptically about the very high rates of return of agricultural R&D reported by some studies in the literature, Alston et al. (2011) try to demonstrate why many of these studies should be treated with caution. In their article they explore the consequences of common modelling choices and their implications for measures of research returns. They demonstrate some important impacts of the choice of certain commonly applied restrictions and the specification choice on findings, but the main finding, however, is consistent across models: a very high social payoff to the investment with very significant state-to-state spillover effects compounding incentive problems and justifying a significant federal role. Nevertheless, the combination of specification choices in their preferred model results in a much lower conventionally measured real internal rates of return to research (i.e., 9% or 10% per annum) compared to those reported typically in previous studies.

Wang, Ball, Fulginiti & Plastina (2012) perform similar research to estimate the contributions of public research to U.S. agricultural productivity growth, using panel data for the 1980 – 2004 period. They model technology by a dual cost function and incorporated own R&D stocks (measured as the cumulation of past research expenditures) as a public (i.e., exogenous) capital input, as well as its interactions with R&D spill-ins from other states, extension activities, and road density. They proceed by estimating a translog cost function using state-by-year panel data. After constructing Törnqvist input and output indices, they derive estimates of productivity growth that capture the impact of local R&D investments as well as the magnifying effects of R&D spill-ins, extension activities, and infrastructure. Their results provide evidence that own R&D, as well as R&D spill-ins, extension activities, and road density, have a positive and significant effect on the productivity of U.S. agriculture. However, they also note that the estimated impact of R&D spill-ins on productivity depends on the model chosen, as is demonstrated by Alston et al. (2011).

Alston, Andersen & Pardey (2015) then turn to the question whether or not there has been a slowdown in the U.S. farm productivity growth lately. The authors examine changes in the pattern of U.S. agricultural productivity growth over the past century, using multifactor and partial-factor productivity estimates. They detect sizable and significant slowdowns in the rate of productivity growth across the 48 states for different periods as shown by Table 2. MFP in 44 of the 48 states has been growing at a statistically slower rate since 1990.

Table 2. Average MFP growth in U.S. agriculture

	1949 - 1990	**1990 – 2007**	**1910 - 2007**
Average MFP growth per year	2.02%	1.18%	1.52%

Source: Alston, Andersen & Pardey (2015).

Using a longer-run national series, productivity growth has slowed since 1990, compared with its longer-run growth rate, which averaged 1.52% per year for the entire period, 1910 – 2007. A cubic time-trend model fits the data very well, with an inflection around 1962. They argue that a series of innovations contributed to a sustained surge of faster-than-normal productivity growth, i.e., a onetime transformation of agriculture throughout the third quarter of the century. They use data obtained by the InSTePP on inputs and outputs in U.S. agriculture to construct Fisher ideal approximations to Divisia indices of quantities of inputs and outputs with adjustments for heterogeneity. Consequently, these quality-adjusted indices are used to estimate and analyse MFP and PFP (of land and labour) measures. The authors rely on a test developed by Zivot & Andrews (1992) to distinguish between a unit root process and a trend stationary process with a structural break of unknown timing, which we refer to as the *ZA*-test. This test allows for a break in either the level or the trend of the underlying series, or both. In their application of the *ZA*-test, the null hypothesis is that the MFP series in natural logarithms has a unit root, while the alternative hypothesis is that the series is stationary around a deterministic trend, with a structural break of unknown timing in its level and trend.

After applying this *ZA*-test on the InSTePP data, Alston et al. (2015) conclude that a significant one-time structural brake in the series does not appear to exist. However, this does not rule out the possibility of a gradual decline in recent decades in the level or growth rate of a fundamentally non-stationary time series. They also use a rolling regressions approach to track down possible breakpoints in the series and they found generally negative dummy variable coefficients for the series of breakpoints following the late 1970's (whereas they used to be positive prior to this period), indicating that, for each breakpoint, productivity was slower after the breakpoint than before. Finally, it is important to note that they also observe high volatilities in the productivity patterns due to unusual weather conditions and changing farm policies, and they suggest that this slowdown came after a period of unusually rapid productivity growth in the middle of the full sample period, 1910 – 2007, with slower rates both in the earlier decades (i.e., 1910–1930) and more recently (1990–2007). Alston, Andersen, and Pardey (2015) conjecture that a wave of technological progress through the middle of the twentieth century – reflecting the progressive adoption of various mechanical innovations, improved crop varieties and animal breeds, synthetic fertilizers and other chemicals, each in a decades long process – contributed to an extended surge of faster-than-normal productivity growth throughout the third quarter of the century, and a subsequent slowdown that has extended into the present era. These authors further speculate that a one-time surge in productivity, like this, could be an inherent feature of the economics of the agricultural transition, the essential feature of which is to shift the majority of the farmers and their families out of agriculture, i.e., a one-time change (Alston, 2018).

Finally, a similar study is performed by Wang, Heisey, Schimmelpfennig & Ball (2015) to determine whether there has been a slowdown in U.S. productivity growth. They criticise several previous studies that suggest U.S. agricultural productivity has slowed by comparing decadal productivity growth rates. Yet, they say, TFP estimates can fluctuate considerably from year to year, largely in response to weather events and other transitory factors. Using arbitrary dates (such as by decade) to break down the sample and make comparisons could give misleading information regarding a productivity slowdown. This study uses historical TFP time series data (1948-2011) obtained by the Economic Research Service (ERS) to evaluate this issue. Their analysis reveals an upward shift in TFP after 1985 and finds no statistical evidence of a productivity slowdown over the last six decades. Other findings are that only a minor growth in total measured use of agricultural inputs occurred during the period 1948 - 2011 and that the extraordinary performance of the U.S. farm sector was driven mainly by increases in TFP, as stated by several studies. Over the last six decades, the mix of agricultural inputs used shifted significantly, with increased use of intermediate goods (e.g., fertilizer and pesticides) and less use of labour and land. The output mix changed as well, with crop production growing faster than livestock production.

2.3.3. Productivity of the EU agriculture

In the following part, we will divert our attention from the U.S. agriculture and introduce some studies concerning the agricultural sector in the European Union and the global agricultural economy. The first article we would like to discuss here is a report made by the European Commission (2014). This brief report shows changes in TFP during the periods 2011 – 2013 and 2005 – 2013. Outputs and inputs are adjusted for quality by weighting their respective volumes by price. In the following paragraphs, we will discuss their main results.

From 2011 to 2013 TFP has increased in some of the new Member States like Bulgaria (+4.7%), Latvia (+4.4%) and Lithuania (+4.3%). Among the old Member States, the highest increase displayed in Belgium (4.6%). On the other hand, TFP declined between 2011 and 2013 in Slovenia (-7%), Malta (-4.7%), Denmark (-3.8%) and Romania (-3.4%).

The average annual change of TFP between 2005 and 2013 varies among the Member States. The most significant decrease was realized by Malta (-7.2%), followed by Denmark (-1.5%), Slovenia (-1.3%), Italy and Luxemburg (-1.1% each), Ireland (-0.8%) and Sweden (-0.3%). Over the same period, TFP stagnated in France, Croatia and in Slovakia, while other Member States realised an increase in TFP over the period 2005- 2013. The most significant growth of TFP can be observed in Romania (+3.8% annually). As regards the different EU-groups, the EU-N13 (+2.1%) produced a rate of growth that was three times higher than in the EU-15 (+0.7%) over the period 2005-2013.

Furthermore, like Alston et al. (2015), the authors also note that yearly changes of TFP are considerably affected by the weather. However, the average annual change in eight consecutive years (2005 – 2013) can indicate a trend. But this paper neither provides any statistical proof for this, nor any explanatory causes. In terms of TFP most of the EU-N13 narrowed the productivity gap and approached the higher TFP level of the EU-15. The main driver of this increase might be in many cases an increasing labour productivity, but also improvements in yields.

In their book, Fuglie, Wang & Ball (2012) report trends in agricultural TFP for eleven EU member states, using data obtained by Ball, Butault, Juan & Mora (2010), which will be discussed in the following paragraph. Figure 7 and Table 3 report the calculated TFP growth rates by sub-periods for the countries and regions in question.

We now turn again to the study performed by Rungsuriyawiboon & Lissitsa (2017) that calculates Malmquist TFP indices for several European countries and was introduced in Paragraph 2.2.4.3. The main results of this study show that technical efficiency scores range from 0.523 by Uzbekistan to maximum 1 with an average of 0.807. There are eight countries in this study, i.e. Bel-Lux, France, Greece, Italy, Netherlands, Hungary, Malta and Croatia showing perfect technical efficiency scores over the entire sample period. The average technical efficiency score implies that the countries in this study were, on average, producing 80.7 percent of the outputs that could be potentially produced using the observed input quantities. For more detailed results for each country, we refer to the paper.

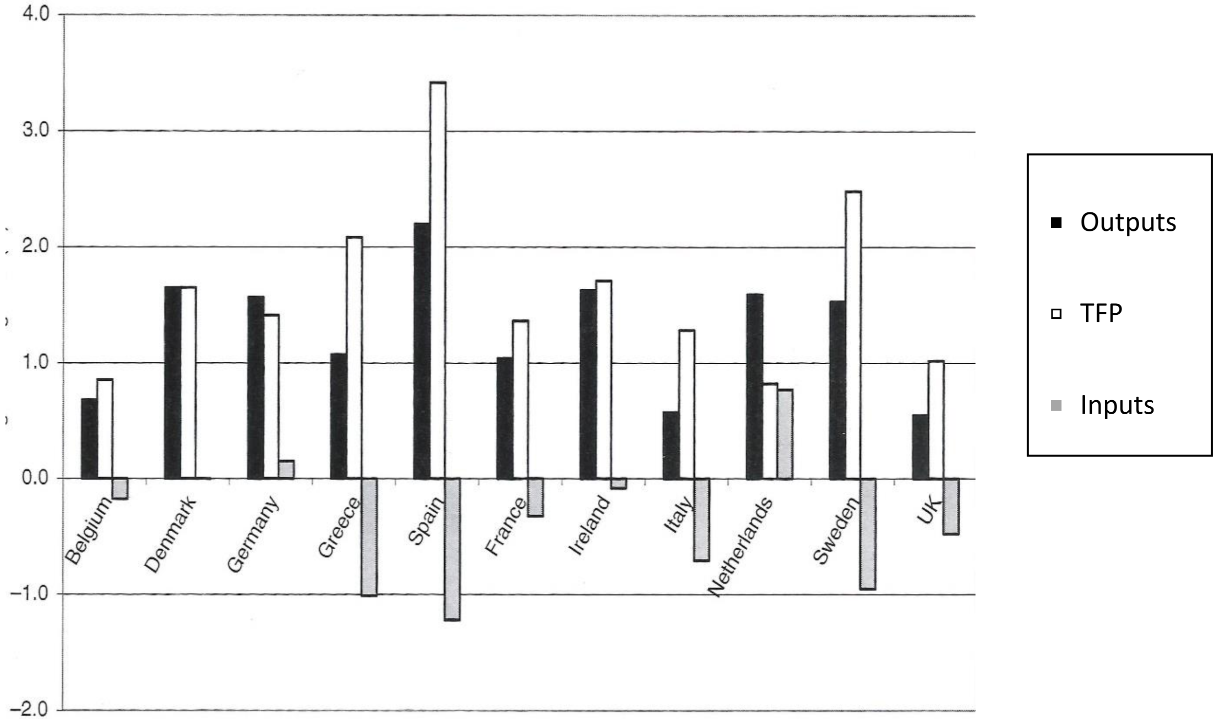

Figure 7. Growth rates for agricultural outputs, TFP and inputs. Average annual growth rate during 1973 – 2002.
Source: Ball, et al. (2010).

Table 3. Trends in agricultural TFP.

Countries	1973 – 1982	1982 – 1992	1992 – 2002	1973 – 2002
Western Europe	1.77	1.36	1.73	1.58
Mediterranean	1.60	1.75	2.87	2.16
Greece	2.78	1.88	1.30	2.08
Italy	-0.56	0.99	3.05	1.28
Spain	4.43	2.78	2.99	3.42
Northern continental	1.76	1.19	1.25	1.29
Belgium	0.18	1.87	1.07	0.86
Denmark	1.72	1.87	0.91	1.65
France	1.70	1.44	1.49	1.36
Germany	2.78	0.47	1.39	1.41
Netherlands	0.54	1.43	0.52	0.82
Others				
Ireland	1.76	2.60	1.25	1.71
Sweden	4.32	1.29	1.50	2.48
UK	1.96	0.58	0.68	1.02

Source: Fuglie, Wang & Ball (2012).

Rungsuriyawiboon & Lissitsa (2017) make some interesting observations that link certain drops or increases in TFP growth of some countries to particular historical events, such as civil wars, the end of the Soviet Union and the BSE (i.e., the Mad Cow disease) and FMD (i.e., the Foot-and-Mouth Disease) crises, which caused negative technical efficiency change in the UK by the end of the 1990's. In order to compare the results for groups of the European countries, the authors divide them into three groups, as shown by Annex 2. The results indicate that the EU15 countries had higher average country technical efficiency compared to the EU10 countries (i.e., young Member States). Average country technical efficiency scores by the transition countries were lower than those by the EU15 and EU10 countries in every single period. The EU10 countries had higher average country technical efficiency than the EU15 countries during the period of 1994 to 1995 and the period of 2000 to 2002. These results suggest during the period of 1994 to 1995 the EU15 countries faced unstable changes after joining the EU leading to lower their technical performance whereas the EU10 countries had to improve their technical performance to impress the former members in order to join the Union in the early twentieth century. The weighted average TFP growth grew at 2.19 percent per annum by countries within the EU15 countries, 2.68 percent per annum by countries within the EU10 countries, 5.10 percent per annum by the transition countries and 3.53 percent per annum by all countries. The results show that countries located within the EU15 countries had average annual growth of the technical and technical efficiency change effects lower than those located within the EU10 and transition countries. This result implies that countries located within the EU10 and transition countries increased the outputs by improving technical efficiency more than those located within the EU15 countries. TFP growth for each group of countries was mainly driven by the technology progress. The contribution of the technical efficiency effect that attributed to TFP growth was quite small by countries located within the EU15 countries while the technical efficiency effect was increased by countries located within the EU15 countries and the transition countries, respectively. The EU15 countries showed technological regress during the period of 1992 to 1993 and a decrease of technical efficiency change during the period of 1997 to 2002. Technological regress could be explained by the reconstruction in Germany, while the Mad Cow disease in the UK may result in a decline of technical efficiency change. The EU10 countries showed a small increase of technical efficiency change during the period of 2000 to 2002 and a modest progress of TFP growth during the period of 1997 to 2002. These results suggest the presence of an anticipation effect on the part of the EU10 countries joining the EU in mid-2004. Transition countries showed an increase of TFP growth over the entire period except the period of 1994 to 1996. This TFP regress was mainly driven by a decline of technical efficiency change. A main reason to explain the TFP regress is that many transition countries were under war and dealt with a political instability during these periods. When comparing TFP growth between the EU15 and transition countries in each period, the EU15 countries showed a high TFP growth rate while the TFP growth of the transition countries was low in that period and vice versa. These results imply that an acceleration of agricultural productivity in Europe over the past decade was driven by each group of the European countries. In conclusion, this study shows that the weighted average TFP growth in the European agriculture over the study period was 3.03%, which was driven by 0.75% in technical efficiency change and 2.27% in technical change.

Another study that constructs Malmquist TFP indices, is conducted by Galanopoulos, Surry & Mattas (2011). Indices are calculated among a set of 32 West European, Central and East

European (CEE) and Middle East and North African (MENA) countries for the period 1961 – 2002. Consequently, the authors look for evidence for convergence of this index among these countries. The results suggest that, despite the fact that the CEE and MENA countries have exhibited a high rate of TFP growth since the 1990s, absolute convergence cannot be confirmed. Evidence for conditional β convergence (which holds if the coefficient of a regression of TFP growth on initial TFP levels is negative) is still found, suggesting that countries tend to converge to their own steady state, and the formation of two separate subsets (or clubs of countries) that converge to different equilibrium points was identified, as can be seen in Annex 3.

The following study (Leetmaa, Arnade & Kelch, 2004) investigates the early consequences of the 1992 CAP reforms that were implemented from 1993 – 1995. Thereby they break the TFP growth indices down into their component parts: efficiency and technical change. As already discussed, efficiency refers to the use of existing inputs. If production is based on an efficient allocation/mix of inputs, any reduction in input use would be expected to result in a reduction in output. In contrast, if production is based on an inefficient allocation/mix of inputs, producers could reduce inputs and maintain the same level of production, or even increase production by more efficient use of their inputs. Technical change embraces many potential sources of productivity growth, including such things as improved seeds, better management techniques, new crop rotation sequences, etc., all of which can reduce per-unit production costs. While they cannot obtain enough data points to reach any definitive conclusions, it appears that the contribution of technical change to productivity growth has slowed since the MacSharry CAP reforms were fully implemented by 1995. It seems that most EU countries continued to experience technology-based productivity growth following the MacSharry reforms, but at a slower rate than before reforms. The authors also note that the majority of countries experienced an increase in their technology-based productivity growth after joining the EU. In conclusion, the authors state that CAP reforms, first begun in 1993, may potentially slow the EU's rate of productivity growth. The U.S. competitive position in global markets could improve under such a trend.

Another and more recent study conducted in light of the impact of the CAP, was performed by Latruffe, Bravo – Ureta, Carpentier, Desjeux & Moreira (2017). Their objective is to examine the association between agricultural subsidies and dairy farm technical efficiency in the EU. A recent meta-analysis of the literature on the relationship between farm technical efficiency and subsidies by Minviel & Latruffe (2017) reports that one-quarter of the models find a significant positive effect of subsidies on technical efficiency, slightly more than half yield a significant negative effect, while the rest report non-significant effects. Latruffe et al. (2017) implement a Cobb-Douglass stochastic production frontier framework (with a single output and four inputs), because they argue it can readily incorporate the technical efficiency component. Note that the stochastic production frontier gives the maximum level of output producible given inputs, the technology and the production environment. Thereby, they develop and apply a Method of Moments (MM) estimation of stochastic production frontiers with endogenous inputs and with explanatory variables influencing technical efficiency. The article uses farm-level data obtained by the EU-FADN for farms located in nine Western European countries for the period 1990 – 2007. According to their results, technological progress exhibits different patterns across countries; they are positive and significant for Denmark, Spain, Portugal, and the United Kingdom, and not significant for Germany and

Ireland. In two countries (i.e., Belgium and Italy) technological progress is first positive and then negative, with a turning point in 1999 for Belgium and 2000 for Italy. Finally, in France, technological progress is negative, but the time coefficients and their square value are of opposite sign, indicating positive technological progress at some point. The calculated turning point would be 2018, which is outside the period under consideration. Consequently, they turn to the inefficiency component and five variables possibly attributing to it, among which there are the share of rented land, the share of hired labour, the debt to asset ratio subsidies, the amount of subsidy received per hectare and its interaction with a dummy included to account for the introduction of decoupling (i.e., the 2003 Luxembourg Reform). Their study yields several interesting results. However, this discussion will here be limited to their main findings only concerning the influence of subsidies, which reveal that the connection between subsidies and technical efficiency is heterogeneous. Hence, they find no uniform effect of CAP subsidies in Western European countries. Despite the subsidies being based on the same rules, they induce different responses from farmers across Europe, suggesting that these responses depend on the local environmental and institutional context. Three countries exhibit lower levels of technical efficiency as subsidy dependence increases, being Belgium, Italy and the United Kingdom. By contrast, their results show that subsidies received by farmers in Spain, Portugal, and in Italy after decoupling have helped them achieve greater technical efficiency. For the remaining countries, no significant impact was found both before and after the introduction of decoupling.

To conclude this section, we would like to mention as well the study done by Ghelfi, Bertazzoli, Marchi, Rivaroli & Samoggia (2012), who consider TFP as an indicator for the degree of sustainability of the agricultural sector of Emilia-Romagna, a region in northeast Italy during the period 2000 – 2009. In particular, they consider productivity gains for three productive systems, relevant for this region: specialist field crops, specialist permanent crops and specialist milk production system. The results reveal a considerable heterogeneity across these different productive systems. In the case of the specialist field crops, the productivity tends to decrease, whereas it progressively rises for specialist permanent crops after an initial low productive period. Finally, the specialist milk production displays an opposite situation. After an initial first period in which there is a good trend of the productive system, the performance progressively goes down only to be inverted by the final years.

2.3.4. Comparison of global agricultural productivity

In this paragraph, several studies that compare productivity and competitiveness across different countries or regions worldwide are reviewed. The first study we would like to mention is conducted by Gopinath, Arnade, Shane & Roe (1997), who compare growth of the agricultural GDP of four major European countries (Denmark, France, Germany and the United Kingdom) with U.S. agricultural growth for the period 1974 – 1993 to investigate their agricultural competitiveness. Their main motivation is to question the common belief that agricultural growth in the EU has been stimulated by high and stable prices that producers received under the CAP, while others believe that output growth is a result of technical change that would continue without price incentives. In order to provide arguments for this debate, the authors decompose growth in agricultural GDP into short run price and input effects versus long run TFP effects. They argue that growth driven by increases in prices/inputs is typically not sustainable in the long run, particularly if policy artificially distorts sector prices upward and otherwise slows the adjustment associated with the competition for economy-wide resources among a country's agricultural and non-agricultural sectors. TFP effects, however, tend to be longer run dynamic sources of growth. Their analysis uses the sectoral GDP function developed by Gopinath & Roe (1995), following Diewert & Morrison (1986), to compute non-parametric estimates of the contributions of both effects to growth in agriculture GDP by applying the Quadratic approximation lemma (Diewert, 1976) to the sectoral GDP function. Therefore, they derive Törnqvist indices of three outputs and eight inputs. Results indicate that TFP is the major source of growth in both the EU and U.S. agricultural sectors during the period 1974-1993. For the U.S., the price effects are significantly negative, while inputs have a small positive contribution to growth during the same period. This relative small contribution from inputs to growth is similar to the EU countries. With the exception of Germany, the effects of agriculture's declining terms of trade with the rest of the economy is relatively lower in the European countries. This, along with large rates of growth in TFP (which vary between 1.7% for the UK and 2.9% for France) has led to relatively large growth rates in GDP. However, since 1988, declining real prices and declining rates of growth in TFP have sharply reduced the growth of European agriculture. In contrast, U.S. agriculture shows a relatively stable growth in its TFP and less adverse effects from declining real prices.

Another study, conducted by Ball, Bureau, Butault & Nehring (2001), calculates TFP indices for nine EU countries and for the U.S. for the period 1973 – 1993, in which the policy environments were relatively stable. The authors use data on input and output prices to construct a bilateral output price index or purchasing power parity, assuming revenue-maximizing behaviour on the part of producers in both countries. According to the authors' estimates, seven of the nine EU countries had TFP levels close to or above that of the U.S. in 1973. The weighted average TFP for the EU-9 grew by 50 percent during this period. However, in the U.S., agriculture productivity grew by approximately 66 percent during this period. When examining this in more detail, they conclude growth in TFP for the EU-9 and the U.S. was similar from 1973 through 1984. From 1985 onwards, growth in TFP for the U.S. was consistently higher than that for the EU-9, resulting in the widening TFP gap. In 2010, this study was updated by Ball et al. to investigate the international competitiveness of agriculture in the EU and the U.S. by calculating relative prices for eleven member states of the EU and the U.S. for the period 1973 – 2002. Therefore, they assume that markets are perfectly competitive and in long-run equilibrium, so that observed prices always equal average total costs, as measured by the cost dual to the production function. Consequently, productivity growth between two points of time for a given country is calculated as the negative of the rate of growth of the output price less the rate of growth in input prices. Their international comparison of relative prices shows that the U.S. was more competitive than its European counterparts throughout the period 1973-2002, except for the years 1973-1974 and 1983-1985. Their results suggest the relative productivity level was the most important factor in determining international competitiveness. Over time, however, variations in exchange rates (the strengthening of the dollar) became more important for international competitiveness [note that these observations are in line with the conclusions made by Gopinath et al. (1997)]. Finally, Ball et al. (2010) note that Sweden and Spain were the only European countries achieving faster rates of productivity growth in agriculture compared to the U.S. According to the authors, this can be explained by the 'advantages of relative backwardness' or the 'catch-up effect' and capital deepening.

An important remark we would like to make regarding the approach of Ball et al. (2010) is the fact that, in our opinion, their assumption of perfectly competitive and in long-run equilibrium markets seems to be highly unlikely, especially for the EU. Thanks to the reform of the CAP, market prices in the EU have decreased, implying that prices don't necessarily reflect average costs. Thus, one should be very careful when defining productivity as the ratio of output prices and input prices (rather than quantities), as possible productivity gains are possibly caused by the CAP reform.

Fuglie (2010) uses the same dataset and also constructed partial factor productivity indices of land and labour productivity to characterize the evolution of productivity growth among Western European countries and regions. The results state that labour productivity grew at an average annual rate of 4.14%. There was, however, an important heterogeneity amongst the different countries and a larger grow was often associated with agriculture that became more capital intensive. The results also suggest that if there was any Western European slowdown in agricultural labour productivity, it seems to have been in the 1980s and not in the more recent decade (1992-2002). Compared to labour productivity, land productivity has grown more slowly at 1.60% per year for Western Europe as a whole. Furthermore, they examine changes in the long-run rates of TFP growth (obtained by Ball et al., 2010) using two tests: the sample-mean difference test and the trend coefficient test. They find that although real agricultural output increased in all countries, the use of inputs declined, and output growth was solely due to TFP growth in most countries. When using 1983 and 1993 as a breakpoint, they cannot find any significant evidence of a slowdown in TFP growth according to the sample-mean difference test. The same conclusions are drawn from the time trend coefficient models. However, it has to be noted that although significant evidence of a global slowdown of TFP growth couldn't be provided, there were considerable regional and national differences, suggesting TFP growth did decline in some regions. Weather-induced fluctuations in output also introduce a serious signal-to-noise problem in constructing valid statistical tests for growth trends. Finally, their analysis of productivity patterns suggests that the slowdown in output growth is entirely due to withdrawals of resources from agriculture, especially labour, and not to a slowdown in productivity growth.

In conclusion, Fuglie (2010) does not find any evidence of a general slowdown in sector-wide agricultural productivity. If anything, he stated, the growth rate in agricultural TFP accelerated in recent decades, in no small part because of rapid productivity gains in several emerging countries, led by Brazil and China, and more recently to a recovery of agricultural growth in the countries of the ex-Soviet bloc. These statements seem to be contradictory to the results obtained by Alston et al. (2015), but the latter only focussed on the agricultural sector in the U.S. Moreover, Fuglie (2010) remarked that his evidence suggests TFP growth may in fact be slowing in developed countries while accelerating in emerging and developing countries. In fact, Alston (2018) addresses these contradictory findings himself by, as he noticed his claims of a slowdown are often contested by many economists concerning its existence, timing and extent (for instance, in Ball, Wang & Nehring, 2010; Wang, 2010; Bal Schimmelpfennig & Wang, 2013; Wang et al., 2015; Fuglie, Clancy, Heisey & MacDonald, 2017). However, Alston (2018) states these studies primarily relied upon data obtained by the Food and Agriculture Organization Corporate Statistical Database (FAOSTAT), which, according to him, is not as good as the datasets prepared by USDA-ERS and InSTePP. In fact, studies using these or similar data have generally rejected the productivity slowdown hypothesis, and more often have reported an acceleration of productivity, especially (but not exclusively) in developing countries. Again, Alston (2018) starts comparing the results according to his methods using these different datasets. Thereby, he finds considerable difference in the time path of productivity change in terms of the overall rate, whether it was accelerating or slowing, and when. He argues the way to measure the price and quantity of capital is the most important source of difference between both databases, and concludes this attributes to the considerable different (and opposing) views of him (i.e., Alston) and other authors.

2.4. Conclusions drawn from the literature review

To end this report, we would like to state our main findings obtained throughout our literature review. Measuring efficiency and productivity has been elaborately discussed throughout the literature. Unfortunately, both terms are often regarded as synonyms, although there is a clear distinction between them, as we have also shown. Both concepts can be measured using parametric and non-parametric methods. One particularly important non-parametric approach is called DEA, for which the Malmquist TFP index has proven to be very useful.

Regarding the empirical studies, productivity analysis is systematically done by determining a common indicator, namely TFP, using indices as a Laspeyres, Paasche, Fisher or Törnqvist index. However, these indices fail to satisfy one or more axioms and therefore they should not be used in an analysis to exhaustively decompose TFP indices into unambiguous measures of technical change and efficiency change. This can be achieved by using the theoretical consistent Lowe TFP index. Secondly, two different approaches are used to measure productivity. Several authors, like Alston (2010) for example, use the ratio of output quantities over output quantities, which strokes with the general definition of productivity. Ball et al. (2010) and similar studies on the other hand, use output prices, assuming that markets are perfectly competitive and in long-run equilibrium, and thus prices should reflect average costs. However, as discussed previously, one has to be careful when assuming that this strong assumption holds for the EU market. Generally, it can be concluded that global TFP increased strongly during the last decade. There is however evidence of a large heterogeneity of the paths followed by different countries/regions: countries that initially had a rapid TFP growth seem to have slowed down during the last decades, whereas less developed countries are catching up rapidly. Providing evidence of a significant slowdown is very hard, as growth can gradually decline, which makes it particularly hard to find breakpoints. It has also been showed that different databases and methods can possibly yield considerably different results for the same indicators of the same country, region and/ or sector. Moreover, considerable problems related to the signal-to-noise concept and to weather induced fluctuations also arise, making the determination of growth trends very complicated. Consequently, when estimating TFP indices, it is important that one is conscious of the consequences of certain assumptions and choices (e.g., the structural form) on findings. Furthermore, although a discussion is going on about the true magnitude of the real internal rate of return of public R&D spending, the obtained results do all unambiguously indicate positive values. This means that R&D is important in fostering TFP growth and that governments have generally been underinvesting in agricultural R&D. A final remark we want to make is that all empirical studies mentioned in this review have adopted a sectoral approach to analyse TFP for a specific U.S. state or EU Member State. Our study however, aims to perform a microeconomic analysis on farm productivity gains, using data obtained by the EU-FADN to construct a cost function and thereby assessing the path and magnitude of individual EU farm productivity gains.

3. Analytical framework

3.1. Cost function approach

As previously discussed, our farm productivity analysis will be based on the estimation of a theoretically consistent flexible multi-input, multi-output cost function using a disaggregated set of input and output categories for individual EU-FADN farms. This section will therefore elaborate upon this theoretical framework.

To introduce the cost function, let total variable cost for farm *f* at time *t* be represented by

$$TC_{ft} = TC\left(w_{ft}, y_{ft}, t; z_{ft}; \alpha\right) + \varepsilon_{0;ft} \, ,$$

(Eq. 19)

for $y \geq 0$, with the usual theoretical properties as described in Paragraph 2.2.4.4.2., where $w_{ft} = \left(w_{1;ft}, \dots, w_{J;ft}\right)$ represents the vector of broad input category prices (with *J* the number of broad input categories), $y_{ft} = \left(y_{1;ft}, \dots, y_{M;ft}\right)$ the vector of broad output category quantities (with *M* the number of broad output categories), $z_{ft} = \left(z_{1;ft}, \dots, z_{K;ft}\right)$ the vector of quasi-fixed broad input quantities (with *K* the number of broad quasi-fixed input categories) and $\varepsilon_{0;ft}$ an error term normally distributed. The dependent variable is obtained as

$$TC_{ft} = \sum_{i=1}^{J} w_{i;ft} \, . \, x_{i;ft} \, ,$$

(Eq. 20)

where $x_{ft} = \left(x_{1;ft}, \dots, x_{J;ft}\right)$ represents the vector of broad input category quantities. Building further on the principles described in Paragraph 2.2.4.4.2, cost minimization based on the cost function (Eq. 19) implies the following system of broad input demand equations

$$x_{i;ft} = x_i\left(w_{ft}, y_{ft}, t; z_{ft}; \alpha\right) + \varepsilon_{i;ft} \, ,$$

(Eq. 21)

where $\varepsilon_{i;ft}$ represents an error term normally distributed. By Shephard's lemma, it holds that

$$x_i(w, y, t; z; \alpha) = \frac{\partial TC(w, y, t; z; \alpha)}{\partial w_i}.$$

The system of broad input demand equations (Eq. 21) is used to estimate the vector of parameters α. Estimated total cost $\widehat{TC}$ and estimated demands for a broad input category $\widehat{x_i}$ are generated as

$$\widehat{TC}_{ft} = TC\left(w_{ft}, y_{ft}, t; z_{ft}; \hat{\alpha}\right)$$
$$\hat{x}_{i,ft} = x_i\left(w_{ft}, y_{ft}, t; z_{ft}; \hat{\alpha}\right) ,$$

subject to

$$y \geq 0$$

$$\hat{x}_i = x_i(w, y, t; z; \hat{\alpha}) \; if \; [(\hat{x}_i > 0) \; and \; (x_i > 0)]$$
$$\hat{x}_i = 0 \; if \; not \; [(\hat{x}_i > 0) \; and \; (x_i > 0)] \,,$$

implying that

$$\widehat{TC}_{ft} \geq \sum_{i=1}^{J} w_{i;ft} \,.\, \hat{x}_{i;ft}.$$

Consequently, we turn our attention to the marginal cost function for broad output category *m*, defined as (whilst leaving aside indices *f* and *t* for clarity)

$$MC_m(w, y, t; z; \alpha) = \frac{\partial TC(w, y, t; z; \alpha)}{\partial y_m} \,,$$

Estimated marginal costs for a broad output category $\widehat{MC}_m$ are generated as

$$\widehat{MC}_{m;ft} = MC_{m;ft}\left(w_{ft}, y_{ft}, t; z_{ft}; \hat{\alpha}\right).$$

From the cost function (Eq. 19), it is then possible to obtain pseudo-observations of the total and average variable costs of each broad output category *m.* Also, pseudo-observations for the demand for broad input category *i* that can be allocated to broad output category *m* can be obtained. For further details on these matters, we refer to the MIMO Deliverable 8 (Henry de Frahan et al., 2015). In practice, these estimations are performed using the performant statistical program Stata (StataCorp, 2017 a).

3.2. SGM specification

3.2.1. Introduction to the SGM functional form

The estimation of the theoretically consistent and flexible multi-input, multi-output cost function uses the Symmetric Generalized McFadden (SGM) functional form that is particularly ideal for applied work. It is a second order Taylor approximation to the unknown total variable cost function. In that sense, the SGM specification is said to be flexible in all its arguments. Under some regularity conditions, flexible cost functions that are twice continuously differentiable in all their arguments are consistent with theory and well-behaved. This is the reason why Paragraph 3.3 details how these regularity conditions can be imposed.

The function is expressed in terms of variable input prices, output quantities and quasi-fixed input quantities. Among the class of flexible quadratic cost functions, the multi-input, multi-output SGM cost function is a function for which the global curvature properties of a cost function can be imposed if needed without destroying its second-order flexibility. Moreover, the SGM form is invariant to normalization and, compared to the popular translog form and generalized Leontief form, imposing global concavity in input prices on the SGM form is easier to implement without imposing unrealistic restrictions on input demand elasticities. The SGM functional form has the additional advantage of being symmetric in its treatment of inputs, but has the disadvantage that its flexibility property is restricted to the actual input prices for which the additional symmetric restrictions are imposed. Its properties are thoroughly described in Diewert & Wales (1987).

3.2.2. Development and use of the SGM functional form in other studies

This paragraph will be dedicated to some important studies that focus either on the development of the SGM functional form, or on its empirical implementation. One of the most important contributions in the development of this flexible functional form, is the work done by Diewert & Wales (1987). They demonstrate that, when using the proposed SGM functional form, imposing the appropriate curvature conditions at one data point imposes the conditions globally, whereas those local techniques frequently fail to yield satisfactory results when using other flexible functional forms. In their paper, they focus on cost functions to produce one output and make use of multiple variable inputs, with time as a fixed input. Concerning the flexibility of the SGM specification, Diewert & Wales (1987) argue that if one imposes linear homogeneity in input prices and symmetry on the second order derivatives for second-order flexibility of the cost function (cf. Paragraph 3.3.1), then the resulting cost function with *J* input prices, a single output quantity and a single time variable must contain at least $\frac{J(J+1)}{2+2J+3}$ free parameters.

This concept, as proposed by Diewert & Wales (1987), is further developed by several other publications. Kumbhakar (1989) uses the SGM functional form to estimate technical efficiency of labour and energy for twelve Finnish foundry plants. Thereby, he adapts the functional form to accommodate for (multiple) fixed inputs, including time. Afterwards, the author also introduces the flexible multiproduct SGM cost function that permits zero values of one or more of the outputs in Kumbhakar (1994). Hence, this framework allows multiple inputs and outputs and considers time as the sole fixed input. The author argues that the global concavity and the linear homogeneity (in prices) properties are satisfied and the function is flexible in the output space. Thus, the function is ideal for estimating, for example, economies of scope, cost complementarity, product-specific returns to scale, etc., without worrying about zero values of output(s), which is not permitted in a translog specification for example, and extrapolations to points far from the point of approximation. He shows that his flexible cost function, with *J* inputs and *M* outputs, requires at least $\frac{J(J+1)}{2} + \frac{M(M+1)}{2} + JM + J + M + 1$ free parameters. Again, as an illustration, a cost function estimation using this functional form, is performed to a panel data of twelve Finnish foundry plants.

Stewart (2009) performs a critical analysis of the framework developed by both Diewert & Wales (1987) and Kumbhakar (1994), as Stewart noticed that the use of the (multiproduct) SGM cost function became increasingly popular. Therefore, he examines the consequences of imposing several conditions and the necessary hypotheses. He states that the major issue is the limited ability to test non-jointness in input quantities (i.e., the notion that there are no cost economies from combining the production in a single enterprise: the costs of multi-output production are the same as the costs of producing the outputs individually) and therefore, careful interpretation is advised when testing for this. For further details, we refer to the paper in question.

We would like to divert our attention now to some empirical studies who apply a (modified) SGM cost function. Rask (1995) estimates a SGM cost function for the Brazilian sugarcane production. Therefore, the author modified the original SGM cost function as proposed by Diewert & Wales (1987) to allow for (multiple) fixed factors of production (i.e., land and capital in their case), apart from multiple inputs and one output. This allows the cost function to be applied to processes which have fixed factors. Hence, it is similar to the framework developed in Kumbhakar (1989). In this paper, the author tries to find evidence of economies of scale and technical change (both of which turned out to be absent or very limited).

Similarly, in Pierani & Rizzi (2003), the authors employ a short-term specification of the SGM cost function capable of accommodating quasi-fixed inputs and variable returns. In their empirical application to a balanced panel of Italian dairy farms, the productive technology consists of one aggregate output, three variable inputs (purchased feed, other intermediate inputs and hired labour) and two quasi-fixed factors (family labour and capital). They find a relatively high rate of cost reduction: 3.5% per year at the panel mean. Technological bias is towards the use of other inputs and economising in hired labour and purchased feeds, while technical efficiency averages 66%.

Peeters & Surry (2000) were able to introduce another interesting feature into the SGM cost function, namely 'price-induced innovation'. They construct a multiple-output SGM cost function, in which technological change is represented by two separate terms. The first term involves the usual time trend representing the date. It operates as a 'shifter' of the input-demand functions (i.e., the gradients of the cost function with respect to input prices). This time trend is intended to reflect the autonomous or exogenous technological developments which are unrelated to price changes. The second term supplements the time trend and involves lagged input prices. This term is supposed to reflect price-induced (endogenous) technological innovation, and operates as an additional shifter of the input-demand equations, given the current input prices, output quantities, and the developments of autonomous technological change. Hence, the study allows to disentangle 'pure' factor substitution, given the state of the technology, from factor substitution due to price-induced changes in technology. Under the conditions of non-jointness in input quantities, the model further allows to identify technological change biases for each output separately. The possibilities of the proposed model are empirically illustrated to time-series data on the feed manufacturing industry in Belgium.

Another empirically orientated study, which is closely related to this work, was conducted by Wieck & Heckelei (2007). They search for evidence on the determinants, cost differentiation and development of short-term marginal costs of dairy farms in important production regions of the EU (under a strict quota regime), using an unbalanced panel data set of the EU-FADN. By performing an estimation of a multi-input, multi-output SGM cost function, they find considerable regional differences in the impact of the outputs, input prices, and quasi-fixed factors on marginal costs. They also formulate and test several hypotheses regarding factors that attribute to significant marginal cost differentiation of farms. In the empirical part of this work, we will also test for some similar hypotheses concerning factors attributing to the rate of (marginal) cost diminution and rate of technical change (see Paragraph 3.4.2). Concerning the specification of the cost function, Wieck & Heckelei (2007) use the functional form as proposed by Diewert & Wales (1987), adding quasi-fixed inputs (Pierani & Rizzi, 2003; Rask, 1995), and following Kumbhakar (1994) and Peeters & Surry (2000) in using a framework with several outputs. Hence, they claim their SGM framework is in line with previous applications of SGM cost functions, even though the simultaneous introduction of multiple outputs, multiple inputs, and several quasi-fixed factors goes beyond previous SGM approaches. Furthermore, the SGM cost function used in this approach is linearly homogeneous, nondecreasing, and concave in input prices. If the respective (estimated) parameter values also imply a nondecreasing function in outputs, the criteria necessary to adequately describe the underlying production technology in a cost-minimizing behavioural framework are fulfilled (Chambers, 1988).

To end this section, we would like to mention as well the work published by Henry de Frahan et al. (2011). During their study, the authors estimate flexible cost functions at the farm level and use them in a farm-level programming model to evaluate the potential supply and income effects of removing milk quotas and gradually reducing producer prices. They make use of an augmented (i.e., cubic) long-run multi-output, multi-input SGM cost function without quasi-fixed inputs. They implement a cubic term to add more flexibility in output response, while conserving the theoretical properties of a well-behaved cost function. This addition allows a U-shaped marginal cost curve. After estimation, the results do confirm the downward sloping marginal cost curves for some dairy farms. Consequently, they embed each farm cost function in a profit-maximisation programming model that is built and calibrated for each farm in the sample. Hence, they were able to simulate how dairy farms without quotas may respond differently to changes in prices and their simulations show that structural changes may take place within the dairy sector for different scenarios. To illustrate: a quota removal with 20 percent reduction in milk prices keeps aggregate milk supply and farm income at about the same level of the 2006 reference year in Belgium. Their micro-simulations also show that quota removal does not necessarily hurt small dairy farms, which is at odds with a more common view.

3.2.3. Implementation of the SGM functional form

As already mentioned multiple times, the cost function *TC* used during this work is also applied in similar ways in other studies conducted by, for example, Wieck & Heckelei (2007); Henry de Frahan et al. (2011) and in the FACEPA Deliverable 9.1 (De Blander et al., 2011). We represent the total cost function to produce L_y goods, using L_x variable inputs and L_z quasi-fixed inputs, as

$$\begin{aligned} TC = {} & (\theta' W)a_1' Y + (\theta' W)a_2' Yt + (\phi' Y)b_1' W + (\phi' Y)b_2' Wt + Y'CW + Z'DW(\phi' Y) \\ & + {}^{1}/_{2}\,(\theta' W)^{-1} W'EW(\phi' Y) + (\theta' W)\{Z'FZ(\phi' Y) + Y'GY + Z'HY\} \\ & + (\theta' W)s'Z(\phi' Y) + (\theta' W)v_1' Zt(\phi' Y) + (\theta' W)(\phi' Y)r't + (\theta' W)v_2' tt(\phi' Y) \end{aligned} \tag{Eq. 22}$$

with the vector of output quantities $Y = \left(y_1, \dots, y_{l_y}, \dots, y_{L_y}\right)'$, the vector of input prices $W = \left(w_1, \dots, w_{l_x}, \dots, w_{L_x}\right)'$ and the vector of quasi-fixed inputs $Z = \left(z_1, \dots, z_{l_z}, \dots, z_{L_z}\right)'$. For readability, the time index $t = 1, \dots, T$ and farm index $f = 1, \dots, F$ are omitted. Note that within this framework, a 'quasi-fixed input' is not regarded as an input that does not vary over time, but as an input that is not (less) responsive to price variations.

The product $(\theta' W)$ can be interpreted as a fixed-weight input price index, with

$$\theta_{l_x} = T^{-1} \sum_{t=1}^{T} \frac{\sum_{f=1}^{F} x_{l_x;ft}}{\sum_{i=i}^{L_x} \sum_{f=1}^{F} x_{i;ft}},$$

where the vector $X = (x_1, \dots, x_{l_x}, \dots, x_{L_x})'$ denotes the vector of input quantities. The input price index is inserted to ensure first-order homogeneity in input prices (cf. property C.4 in Paragraph 2.2.4.4.2).

Similarly, the product $(\phi' Y)$ can be interpreted as a fixed-weight output quantity index, with

$$\phi_{l_y} = T^{-1} \sum_{t=1}^{T} \frac{\sum_{f=1}^{F} p_{l_y;ft}}{\sum_{i=i}^{L_y} \sum_{f=1}^{F} p_{i;ft}},$$

where the vector $P = (p_1, \dots, p_{l_y}, \dots, p_{L_y})'$ denotes the vector of output prices. The output quantity index is inserted to ensure the regularity condition $TC(Y = 0, W, Z) = 0$ (cf. property C.6 in Paragraph 2.2.4.4.2).

Consequently, by applying Shephard's lemma, we can construct the system of equations, i.e. the set of input demand equations, that will actually be estimated:

$$x_{l_x} = \frac{\partial TC}{\partial w_{l_x}}$$

$$\begin{aligned} x_{l_x} = {} & \theta_{l_x} a_1' Y + \theta_{l_x} a_2' Y t + (\phi' Y) b_{1,l_x} + (\phi' Y) b_{2,l_x} t + Y' C_{l_x} + Z' D_{l_x} (\phi' Y) \\ & + (\theta' W)^{-1} \{ W' E_{l_x} - {}^{1}\!/_{2}\, \theta_{l_x} (\theta' W)^{-1} W' E W \} (\phi' Y) \\ & + \theta_{l_x} \{ Y' G Y + (\phi' Y) Z' F Z + Z' H Y \} + \theta_{l_x} s' Z (\phi' Y) + \theta_{l_x} v_1' Z t (\phi' Y) \\ & + \theta_{l_x} (\phi' Y) r t + \theta_{l_x} v_2' t t (\phi' Y) , \end{aligned}$$

(Eq. 23)

where the observed input quantities x_i are equated with the optimal input quantities $\frac{\partial TC}{\partial w_{l_x}}$, i.e., those that minimize total costs. Note that observed input quantities x_i must be strictly positive since Shephard's lemma does not hold in a corner solution.

3.3. Properties of the cost function and imposed conditions

3.3.1. Flexibility

The concept of flexibility was introduced in Paragraph 2.2.4.4.2 and we have already stated the specified cost function is a second order Taylor approximation to the unknown total variable cost function. In that sense, the SGM specification is said to be flexible in all its arguments. Under some regularity conditions, flexible cost functions that are twice continuously differentiable in all their arguments are consistent with theory and well-behaved. The studies upon which this work is strongly based (i.e., De Blander et al., 2011 and Henry de Frahan et al., 2015), use cost function specifications that are however not fully flexible in all their arguments. In order to address this issue, several terms present in Equation 22 were implemented specifically for this work, in contrast to the cost function specifications used in these previous papers. The following equation is identical to Equation 22, however, the terms written in red are the terms that were added in addition to the cost function used in the MIMO Deliverable 8 (Henry de Frahan et al., 2015):

$$
\begin{aligned}
TC = (\boldsymbol{\theta}'\boldsymbol{W})\boldsymbol{a}_1'\boldsymbol{Y} + (\theta'W)a_2'Yt + (\boldsymbol{\phi}'\boldsymbol{Y})\boldsymbol{b}_1'\boldsymbol{W} + (\phi'Y)b_2'Wt + Y'CW + Z'DW(\phi'Y) \\
+ {}^1\!/_2\,(\theta'W)^{-1}W'EW(\phi'Y) + (\theta'W)\{Z'FZ(\phi'Y) + Y'GY + Z'HY\} \\
+ (\boldsymbol{\theta}'\boldsymbol{W})\boldsymbol{s}'\boldsymbol{Z}(\boldsymbol{\phi}'\boldsymbol{Y}) + (\boldsymbol{\theta}'\boldsymbol{W})\boldsymbol{v}_1'\boldsymbol{Zt}(\boldsymbol{\phi}'\boldsymbol{Y}) + (\boldsymbol{\theta}'\boldsymbol{W})(\boldsymbol{\phi}'\boldsymbol{Y})\boldsymbol{r}'\boldsymbol{t} \\
+ (\boldsymbol{\theta}'\boldsymbol{W})\boldsymbol{v}_2'\boldsymbol{tt}(\boldsymbol{\phi}'\boldsymbol{Y})\,.
\end{aligned}
$$

In doing so,

- we take account for variation in quasi-fixed inputs through time by adding a time trend to the quasi-fixed inputs *Z*; hence we fulfil the second-order flexibility in (quasi-)fixed inputs,
- we add the correct time-independent variables,
- the cost function fulfils second-order flexibility in time as well, by adding the time coefficient in square.

Hence, this function is now said to be fully flexible. We note as well that our functional form is close to parsimony, but not fully parsimonious[2].

3.3.2. Separability

Within this framework, we assume the functional separability of (broad) output and input categories. The theoretical concept of separability was already introduced during our literature review. Practically, partition in inputs and outputs is performed as the following. As a rule of thumb, Sato (1967) recommends to aggregate individual inputs that are similar in techno-economics characteristics. One of such similarities is the ease of substitution. In that respect, 'wages' and 'contract work' inputs are part of the same 'services' input category for instance. In this case, intra-class direct elasticities of substitution are substantially higher than the inter-class direct elasticities. Another similarity can also be the strong complementarity. In that respect, fertiliser, pesticide and seed inputs can be aggregated within the 'crop-specific inputs' category, and machinery and energy inputs within the 'other inputs' category for instance. In that case, intra-class direct elasticities of substitution are substantially smaller than the inter-class direct elasticities. The extent to which this general conventional assumption introduces an aggregation bias depends on the extent to which technical change is neutral with respect to individual inputs (Sato, 1967). Notwithstanding this practicality, separability in inputs requires that the marginal rate of substitution (MRS) between two inputs in one input aggregate be independent of any other input outside their aggregate. In analogy with this practical input aggregation, individual outputs that are similar in techno-economics characteristics are aggregated together in the same output aggregate. When one of such similarities is the ease of transformation because of a common underlying technology (Bailey & Friedlaender, 1982), then wheat and other cereals are aggregated within the 'cereals' category for instance. In this case, intra-class direct elasticities of transformation are substantially higher than the inter-class direct elasticities. When another possible similarity is the strong complementarity among individual outputs, then cow milk and cow meat are aggregated within the 'bovine outputs' category for instance. In that case, intra-class direct elasticities of transformation are substantially smaller than the inter-class direct elasticities. The extent to which this general conventional assumption introduces an aggregation bias also depends on the extent to which technical change is neutral with respect to individual outputs.

[2] A functional form is parsimonious if it can provide a second-order approximation using a minimal number of parameters (Diewert and Wales, 1995). For parsimony in parameters, the resulting cost function with J input prices, M output quantity, K fixed inputs, and one time variable must contain just J(J+1)/2 + M(M+1)/2 + K(K+1)/2 + JM + JK + MK+ J + M+ K + 1 free parameters.

Notwithstanding this practicality, separability in outputs requires that the marginal rate of transformation (MRT) between two outputs in one output aggregate be independent of any other output outside their aggregate.

In other words, the separability assumption is acceptable to the extent that outputs sharing a similar underlying technology are grouped together in the same broad output category during the data aggregation process, such that the technology of producing these outputs in one particular broad output category is separate from the technology of producing outputs belonging to another broad output. This implies that producing one output belonging to a broad output category cannot directly affect producing another output that belongs to another broad output category. It can only affect indirectly producing this other output through producing the broad output category to which it belongs. For instance, wheat and maize belong to the same broad output category 'cereals' and share the same technology, while dry pulses and oilseeds, belonging to another broad output category 'dry pulses & oilseeds', share another technology. Producing wheat cannot directly affect producing dry pulses through transformation effects, only indirectly if producing more wheat leads to producing more cereals and, hence, through transformation effects less dry pulses & oilseeds and, in turn, less dry pulses. The aggregation scheme adopted in this work will be discussed in detail in Paragraph 4.5.

3.3.3. Symmetry and adding-up restrictions

We apply the symmetry restrictions on the elements of matrices E, F and G. In other words, we impose the coefficients with permuted indices to be identical:

$$\begin{aligned} &e_{ij} \equiv e_{ji}, && i,j = 1, \dots, L_x \\ &f_{kl} \equiv f_{lk}, && l,k = 1, \dots, L_z \\ &g_{mn} \equiv g_{nm}, && m,n = 1, \dots, L_y. \end{aligned}$$

The adding-up constraint is ensured by

$$\sum_{j=1}^{L_x} e_{ij}\,, \qquad i = 1, \dots, L_x.$$

For further details, we refer to Diewert & Wales (1987). Note that these restrictions are always imposed during the estimations in the empirical part of this work (see section 5).

3.3.4. Monotonicity conditions

3.3.4.1. General remark on monotonicity

As mentioned before, a well-behaved cost function should be non-decreasing in output quantities, non-decreasing in input prices (i.e., the input demands cannot be negative) and non-increasing in fixed inputs (Chambers, 1988). These conditions will be further elaborated one-by-one in the following paragraphs. Concerning the empirical part of this work (section 5), we note that the proposed framework, as coded in Stata, allows the possibility to impose all monotonicity conditions, it is however not recommended to impose both monotonicity and curvature of input prices or both monotonicity and curvature of quasi-fixed inputs. Since the SGM is truncated Taylor series in *w* and *z*, it is simply impossible to impose that the cost function is globally non-decreasing in input prices, while at the same time being concave in input prices. Wolff, Heckelei & Mittelhammer (2004) make a similar observation.

3.3.4.2. Non-negativity of every MC_{l_y} for the SGM

The first monotonicity condition requires a well-behaved cost function to be non-decreasing in output quantities. This is equivalent to imposing that marginal costs for each output l_y should be positive. The marginal cost for output l_y can be written as

$$\begin{aligned}MC_{l_y} = (\theta'W)a_{1,l_y} + (\theta'W)a_{2,l_y}t + b_1'W\phi_{l_y} + b_2'Wt\phi_{l_y} + C_{l_y}'W + Z'DW\phi_{l_y} \\ + {}^1\!/_2\,(\theta'W)^{-1}W'EW\phi_{l_y} + (\theta'W)\left\{Z'FZ\phi_{l_y} + 2Y'G_{l_y} + Z'H_{l_y}\right\} \\ + (\theta'W)s'Z\phi_{l_y} + (\theta'W)v_1'Zt\phi_{l_y} + (\theta'W)r't\phi_{l_y} + (\theta'W)v_2'tt\phi_{l_y},\end{aligned}$$

where the vector $C_{l_y} = (c_{l_y1}, c_{l_y2}, \dots, c_{l_yL_x})'$, the vector $G_{l_y} = (g_{l_y1}, g_{l_y2}, \dots, g_{l_yL_x})'$ and the vector $H_{l_y} = (h_{l_y1}, h_{l_y2}, \dots, h_{l_yL_x})'$.

Consequently, the l_y restrictions $MC_{l_y} \geq 0$ can be implemented as

$$\begin{aligned}c_{l_y1} \geq -\min_{obs}\Bigg[&\frac{(\theta'W)a_{1,l_y} + (\theta'W)a_{2,l_y}t + b_1'W\phi_{l_y} + b_2'Wt\phi_{l_y} + C_{l_y(-1)}'W_{(-1)}}{w_1} \\ &+ \frac{Z'DW\phi_{l_y} + {}^1\!/_2\,(\theta'W)^{-1}W'EW\phi_{l_y} + (\theta'W)\left\{Z'FZ\phi_{l_y} + 2Y'G_{l_y} + Z'H_{l_y}\right\}}{w_1} \\ &+ \frac{(\theta'W)s'Z\phi_{l_y} + (\theta'W)v_1'Zt\phi_{l_y} + (\theta'W)r't\phi_{l_y} + (\theta'W)v_2'tt\phi_{l_y}}{w_1}\Bigg],\end{aligned}$$

where the symbol $W_{(-1)}$ denotes the vector W, with the first element removed.

We would like to quote here Fletcher (1993), that, in general, a "bound $c_{l_y1} \geq 0$ can be removed by defining a new parameter $\tilde{c}_{l_y1}$ which replaces c_{l_y1}, such that

$$c_{l_y1} = \tilde{c}_{l_y1}^2.$$

Then, for any $\tilde{c}_{l_y1} \in (-\infty, \infty)$ it follows that $c_{l_y1} \geq 0$, so the bound does not need to be explicitly enforced. […] For strict constraints $c_{l_y1} > 0$ it is possible to use $c_{l_y1} = \exp(\tilde{c}_{l_y1})$. The advantage of these transformations is that they do extend the range of problems which can be handled by an unconstrained minimization routine". When the bound takes on the form $c_{l_y1} \geq \kappa$, with $\kappa \in (-\infty, \infty)$ a constant, it can be removed by defining a new parameter $\tilde{c}_{l_y1}$ which replaces c_{l_y1}, such that

$$c_{l_y1} = \tilde{c}_{l_y1}^2 + \kappa.$$

Then, for any possible value the new parameter $\tilde{c}_{l_y1}$ takes, the inequality $c_{l_y1} \geq \kappa$ is automatically fulfilled. We thus write the parameter c_{l_y1} as the sum of the constant right-hand side, κ, plus some positive amount $\tilde{c}_{l_y1}^2$, and optimize the objective function over $\tilde{c}_{l_y1}$ resulting in the estimator with respect to the new parameter $\tilde{c}_{l_y1}$. The old parameter c_{l_y1} is guaranteed to have such a value that $MC_{l_y} \geq 0$ at all observed data points, as it can be recovered by

$$c_{l_y1} = \tilde{c}_{l_y1}^2 - \min_{obs}\left[\frac{(\theta'W)a_{1,l_y} + (\theta'W)a_{2,l_y}t + b_1'W\phi_{l_y} + b_2'Wt\phi_{l_y} + C_{l_y(-1)}'W_{(-1)}}{w_1} + \frac{Z'DW\phi_{l_y} + {}^1\!/_2\,(\theta'W)^{-1}W'EW\phi_{l_y} + (\theta'W)\left\{Z'FZ\phi_{l_y} + 2Y'G_{l_y} + Z'H_{l_y}\right\}}{w_1} + \frac{(\theta'W)s'Z\phi_{l_y} + (\theta'W)v_1'Zt\phi_{l_y} + (\theta'W)r't\phi_{l_y} + (\theta'W)v_2'tt\phi_{l_y}}{w_1}\right]$$

3.3.4.3. Non-negativity of every input demand x_{l_x}

The second condition requires a well-behaved cost function to be non-decreasing in input prices. Thus, the demand for each input l_x (given by Equation 23) cannot be negative. Following the same reasoning as above, imposing a positive input demand can be obtained by the re-parametrization

$$c_{1l_x} = \tilde{c}_{1l_x}^2 - \min_{obs}\left[\frac{\theta_{l_x}a_1'Y + \theta_{l_x}a_2'Yt + (\phi'Y)b_{1,l_x} + (\phi'Y)b_{2,l_x}t + \sum_{l_y=2}^{L_y} y_{l_y}c_{l_yl_x}}{y_1} + \frac{Z'D_{l_x}(\phi'Y) + (\theta'W)^{-1}\{W'E_{l_x} - {}^1\!/_2\,\theta_{l_x}(\theta'W)^{-1}W'EW\}(\phi'Y)}{y_1} + \frac{\theta_{l_x}\{Y'GY + Z'F(\phi'Y)Z + Z'HY\} + \theta_{l_x}s'Z(\phi'Y)}{y_1} + \frac{\theta_{l_x}v_1'Zt(\phi'Y) + \theta_{l_x}(\phi'Y)rt + \theta_{l_x}v_2'tt(\phi'Y)}{y_1}\right].$$

3.3.4.4. Non-increase of TC in quasi-fixed inputs

The third monotonicity condition states that the cost function should not increase in quasi-fixed inputs. Therefore, we need the derivative of the cost function (Equation 22) with respect to quasi-fixed input l_z to be negative. The derivative is given by

$$\frac{\partial TC}{\partial z_{l_z}} = D_{l_z}W(\phi'Y) + 2(\theta'W)F_{l_z}Z(\phi'Y) + (\theta'W)H_{l_z}Y + (\theta'W)s_{l_z}(\phi'Y) + (\theta'W)v_{1,l_z}t(\phi'Y).$$

Again, we can impose the restriction that this derivative should be negative, by to following re-parametrization

$$d_{l_z1} = -\tilde{d}_{l_z1}^2 - \max_{obs}\left[\frac{D_{l_z(-1)}'W_{(-1)}(\phi'Y) + 2(\theta'W)F_{l_z}Z(\phi'Y) + (\theta'W)H_{l_z}Y}{w_1(\phi'Y)} + \frac{(\theta'W)s_{l_z}(\phi'Y) + (\theta'W)v_{1,l_z}t(\phi'Y)}{w_1(\phi'Y)}\right]$$

3.3.5. Curvature conditions

3.3.5.1. General remark on curvature

The curvature conditions will be discussed in a similar way as the monotonicity conditions. A well-behaved cost function fulfils the following requirements: concavity of *TC* in inputs prices, convexity of *TC* in quasi-fixed inputs and convexity of *TC* in output quantities (Chambers, 1988). We would like to note again that, while our framework allows to impose all curvature conditions, it is not recommended to impose both monotonicity and curvature of input prices or both monotonicity and curvature of quasi-fixed inputs due to the same reasoning as mentioned in Paragraph 3.3.4.1.

3.3.5.2. Concavity of TC in input prices

A well-behaved cost function should be concave in input prices. This condition requires the Hessian matrix $\frac{\partial^2 TC}{\partial w \partial w'}$ to be negative semi-definite, a condition that holds by requiring the matrix *E* to be negative semi-definite. Now this restriction needs to be combined with the adding-up constraint (Diewert & Wales, 1987). For example, by writing a 4 x 4 negative semi-definite matrix *E* as the product of its Cholesky factors $\mathfrak{L}_E$ and $\mathfrak{L}'_E$

$$
\begin{aligned}
E &= -\mathfrak{L}_E . \mathfrak{L}'_E \\
&= \begin{pmatrix}
l_{11}^2 & l_{11}l_{21} & l_{11}l_{31} & l_{11}l_{41} \\
l_{11}l_{21} & l_{21}^2 + l_{22}^2 & l_{21}l_{31} + l_{22}l_{32} & l_{21}l_{41} + l_{22}l_{42} \\
l_{11}l_{31} & l_{21}l_{31} + l_{22}l_{32} & l_{31}^2 + l_{32}^2 + l_{33}^2 & l_{31}l_{41} + l_{32}l_{42} + l_{33}l_{43} \\
l_{11}l_{41} & l_{21}l_{41} + l_{22}l_{42} & l_{31}l_{41} + l_{33}l_{42} + l_{33}l_{43} & l_{41}^2 + l_{42}^2 + l_{43}^2 + l_{44}^2
\end{pmatrix},
\end{aligned}
$$

we have that the adding-up constraint results in following restrictions on the elements of the Cholesky factors

$$
\begin{aligned}
l_{41} &= -(l_{11} + l_{21} + l_{31}) \\
l_{42} &= -(l_{22} + l_{32}) \\
l_{43} &= -l_{33} \\
l_{44} &= 0.
\end{aligned}
$$

In other words, the columns of *L* sum to zero or, in general, $\sum_{i=1}^{I} l_{ij} = 0$.

3.3.5.3. Convexity of TC in quasi-fixed inputs

The second convexity condition for a well-behaved cost function is that it should be convex in quasi-fixed inputs. Convexity of the cost function in quasi-fixed inputs requires the Hessian matrix $\frac{\partial^2 TC}{\partial z \partial z'}$ to be positive semi-definite, a condition that holds by requiring the matrix *F* to be positive semi-definite, which is ensured by writing it as the product of its Cholesky factors:

$$F = \mathfrak{L}_F . \mathfrak{L}'_F.$$

3.3.5.4. Convexity of TC in output quantities

The final condition concerning convexity/concavity of a well-behaved cost function is the convexity of the SGM cost function in output quantities. This requires that the Hessian matrix

$\frac{\partial^2 TC}{\partial y \partial y'}$ be positive semi-definite, a condition that holds by requiring the matrix G to be positive semi-definite, which is ensured by writing it as the product of Cholesky factors:

$$G = \mathfrak{L}_G \,.\, \mathfrak{L}_G'.$$

3.4. Indicators and determinants

3.4.1. Calculation of different indicators

After estimation of the cost function, we are able to retrieve the following indicators of cost and technical change, as described in Paragraph 2.2.4.4.4:

- rate of marginal cost diminution (indicated as *RMCD* hereafter), which is computed for each output category l_y

$$RMCD_{l_y} = -\frac{\partial MC_{l_y}}{\partial t} MC_{l_y}^{-1}$$

  - ➢ $RMCD > 0$ implies that marginal costs diminish over time

- rate of (total) cost diminution (indicated as *RCD* hereafter)

$$RCD = \theta(w, y, t) = -\frac{\partial TC}{\partial t} TC^{-1}$$

  - ➢ $RCD > 0$ implies that total costs diminish over time

- rate of technical change (indicated as RTC hereafter)

$$RTC = \tau(x_1, \dots, x_I, t) = \frac{\partial \ln f(x_1, \dots, x_I, t)}{\partial t}$$

$$RTC^3 = \varepsilon^*(w, y, t) * RCD = \frac{TC}{y \sum_{m=1}^{M} MC_m} * RCD$$

  - ➢ $RTC > 0$ implies that production increases over time, while holding inputs constant

- factor-biased technical change (indicated as *FBTC* hereafter), which is computed for each input category l_x

$$FBTC_{l_x} = \frac{\partial \ln x_i \,(w_1, \dots, w_I, y_1, \dots, y_M, t)}{\partial t}$$

  - ➢ $FBTC > 0$ implies that the technical change is input l_x saving.

In addition, we would like to discuss briefly how economies of scale and scope can be examined within this framework. Following Kumbhakar (1994), we define the following indicators:

- overall returns to scale (indicated as *ORTS* hereafter)

$$ORTS = \left\{ \sum_{l_y=1}^{L_y} \frac{\partial \ln TC}{\partial \ln y_{l_y}} \right\}^{-1} = \frac{TC}{\sum_{l_y=1}^{L_y} y_{l_y} MC_m}$$

  - ➢ $ORTS > 1$ implies that there are economies of scale

[3] $\varepsilon^*(w, y, t)$ indicates the size elasticity. This equation is thoroughly discussed in paragraph 2.2.4.4.4. For further details, we refer to Chambers (1988).

- product-specific returns to scale (indicated as $PSRTS$ hereafter), which is computed for each output category l_y

$$PSRTS_{l_y} = \frac{TC\left(y_1, \dots, y_{l_y-1}, y_{l_y}, y_{l_y+1}, \dots, y_{L_y}\right) - TC\left(y_1, \dots, y_{l_y-1}, 0, y_{l_y+1}, \dots, y_{L_y}\right)}{y_{l_y} MC_{l_y}}$$

  - ➢ $PSRT_{l_y} > 1$ (economies of scale in output l_y), means that total incremental costs will rise less than proportionately as y_{l_y} increases.

- economies of scope (indicated as *ESCP* hereafter)

$$ESCP = \frac{\sum_{l_y=1}^{L_y} TC(0, \dots, 0, y_{l_y}, 0, \dots, 0)}{TC(y_1, \dots, y_{L_y})}$$

  - ➢ $ESCP > 1$ (if economies of scope are present), implies that for a given output mix, a farm producing all the outputs will have lower costs than farms producing only one output l_y.

In section 5 of this work, the indicators listed above will be estimated and analyzed for crop farms in the three most important regions for cereal production of the EU.

3.4.2. Determinants underlying measured productivity gains

Once we have retrieved the estimated values of RMCD, RCD and RTC, we attempt to identify and quantify different factors attributing to these rates. In what follows, we formulate different hypotheses *ex-ante*, inspired by Wieck & Heckelei (2007). Thereby, we will cite and discuss these hypotheses, along with the implemented methods to validate these hypotheses. For further details on the description and calculation methods of the different variables used as determinants, we refer to section 4.5 of this work and the MIMO Deliverable 8 (Henry de Frahan et al., 2015). Besides, Annex 4 provides an overview concerning several variables, directly retrieved from the EU-FADN dataset, for the computation of several of these determinants. Other required variables that are not mentioned in Annex 4 can be directly derived after the data aggregation process.

Hypothesis 1: Larger farms will have higher rates of cost diminution and technical change.
Compared with small farms, large farms can benefit from technological economies of scale and lower input prices. They might be able to adopt new technologies sooner (for example, invest in expensive automation equipment). Concerning the indicators for farm size available in our EU-FADN dataset, we use the net total utilizable agricultural area, abbreviated as 'TUAA' (expressed in ha) for crop farms. This indicator is calculated as the TUAA subtracted with the land leased to others. For dairy farms, we use the number of dairy cows, expressed as livestock units (LU) as an indicator for farm size. Finally, for cattle farms, we use the variable 'Other cattle' (also expressed in LU).

Hypothesis 2: More specialized farms have higher rates of cost diminution and technical change compared to less specialized farms.
The degree of farm specialization is often considered to be strongly related to cost-minimizing behavior. We expect that specialized farms have good access to (new) technology and – probably even more important – show on average better performance in managing the production process. Large-scale, specialized producers can probably further strengthen their ability to produce at low costs, but small highly specialized farms can also keep their costs at

low level under favorable production conditions (Colman & Harvey, 2004; Dorsch, 2002). For the degree of crop farm specialization, we take the ratio of aggregated crop-specific output (e.g. cereal output) over total aggregated farm output. For dairy farms, we take the ratio of dairy output (consisting of both milk and milk products) over total aggregated farm output and for cattle farms, we take the aggregate animal-specific output over total farm output.

Hypothesis 3: Farms with relatively more capital per labour unit will have higher rates of cost diminution and technical change.
We expect farms that are relatively more capital intensive to adopt new and more technology sooner compared to very labour intensive farms This might lead higher estimated values of RCD, RTC and RMCD. For the indicator used to validate this hypothesis, we compute the variable 'Capital per AWU' (i.e., annual work unit) for each farm category by dividing the yearly value of non-land assets contributing to production by the total labour input in AWU.

Hypothesis 4: Farms with relatively more capital per size unit will have higher rates of cost diminution and technical change.
Similarly to the previous hypothesis, we expect farms with relatively higher rates of capital per land or livestock units to be more successful in reducing their costs and to have higher rates of technical change. Therefore, we use the ratio of the yearly value of non-land assets contribution to production and the same indicator for farm size as used for testing the first hypothesis for the different farm types.

Hypothesis 5: Crop farms with relatively more agricultural land in ownership will have higher rates of cost diminution and technical change.
We would like to verify whether farmers invest more or in their own crop lands or take more care of it, compared to lands they rent from others, which would contribute to higher productivity gains. Land ownership might give a farmer more incentives to manage the land in a more sustainable way. Moreover, it gives a farmer a certain guarantee that his own efforts (e.g., long-term sustainable agricultural practices, investing in irrigation infrastructures, etc.) will be profitable for himself in the long run. If he risks losing the land he rents the following year, he won't be tempted to make huge efforts in conserving, protecting and investing in these lands. This concept is also known as 'land tenure security'. To test this hypothesis, we will verify the correlation between RMCD, RCD and RTC, and the landownership ratio. The latter is computed as the ratio of the own utilized agricultural area (in ha) or OUAA (which is the TUAA subtracted with the UAA rented by the holder under a tenancy agreement for a period of at least one year) and the TUAA.

Hypothesis 6: Dairy and cattle farms with a higher stocking density per ha will have higher rates of cost diminution and technical change.
Stocking density per ha of ruminant grazing livestock is defined by the EU-FADN as the average number of bovine LU (except calves for fattening) and sheep/goats per hectare of forage UAA. Forage area includes fodder crops, agricultural fallows and land withdrawn from production (not cultivated, except in the exceptional cases of crops under set-aside schemes). According to this hypothesis, dairy and cattle farms with a higher stocking density per ha will have a higher RCD,RTC and RMCD, which could be explained by the argument that more intensive livestock farming and dairy farming leads to more/better technology and better performances in managing the herd.

Hypothesis 7: Dairy and cattle farms with a higher share of grassland in TUAA will have lower rates of cost diminution and technical change.

This hypothesis is closely related to hypothesis 6, as it is assumed that less intensive animal farming leads to inferior performances. In order to test this statement, we compute the 'grassland ratio' as the ratio of aggregated input of grassland (i.e., the yearly use value of rented, debt-free and indebted grassland contributing to production) over the sum of aggregated input of grassland and crop land (i.e., the yearly use value of rented, debt-free and indebted cropland contributing to production).[4]

Hypothesis 8: If a large fraction of a farm's costs is covered by subsidies, the rate of cost diminution and technical change of this farm will be relatively low.

The basis for this hypothesis lies in the assumption that a farm's manager might be less careful with the expenditures he has to make. Hence, receiving a great amount of subsidies might lower one's incentives to reduce costs to an absolute minimum. In our dataset, we construct the variable 'Subsidy ratio' as the ratio of total subsidies received on current operations linked to production (i.e., excluding on investment), over the total aggregated costs for each farm.

Hypothesis 9: An intensive use of crop-specific inputs (i.e., fertilizer, pesticides, seeds, etc.) will attribute to higher rates of cost diminution and technical change.

We expect the crop farms that are characterized by having a high degree of intensification in their use of chemicals, to have higher RCD and especially RTC, because those inputs are expected to be highly efficient in their contribution to the production process. On top of that, the continuous research and development of these inputs might attribute to outstanding productivity gains as well. Therefore, we compute the share of these inputs (i.e., seeds, fertilizers, pesticides and other specific crop inputs) in the total variable input expenditures as an indicator of the intensification of the crop production.

Hypothesis 10: The rates of cost diminution and technical change will differ among different subregions.

It is not unlikely to assume that location-bound factors will have a significant impact on RCD and RTC. These factors might include local policies, cooperative associations, climate and soil conditions, etc. For this reason, we constructed a dummy variable for each subregion at the NUTS 2 level[5].

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[4] In Wieck & Heckelei (2006), this indicator is also used to gain some insight into marginal cost differentiation of dairy farms depending on their location. The dataset used for their study did not contain more specific information about the characteristics of farms' locations and thus, they relied upon the correlation between the grassland ratio and differences in farm location to examine the impact the latter has on cost differentiation. They argue that differences in farm locations may result in variable cost variations due to, for example, higher expenses for variable inputs or machinery under unfavourable production conditions in grassland or mountainous regions.

[5] NUTS refers to the Classification of Territorial Units for Statistics (derived from the French equivalent 'Nomenclature des unités territoriales statistiques'), which is a geocode standard for referencing the subdivisions of countries for statistical purposes. This standard is developed and regulated by the EU.

Hypothesis 11: The rates of cost diminution and technical change increase over time (at constant variable input prices).
Due to exogenous technological developments, we expect the RCD, RTC and RMCD to increase progressively year by year, as, although heavily disputed by several authors, it has not yet been impeccably proven in the literature that there is a slowdown in productivity growth. Therefore, we construct dummy variables for the different years of observation.

Hypothesis 12: Farms with higher yields have higher rates of (marginal) cost diminution and technical change compared to farms with lower yields.
In Wieck & Heckelei, the authors verify whether milk yields attribute to lower marginal costs in dairy production, as milk yields are commonly perceived to be one of the most important cost indicators (e.g., Colman & Harvey, 2004; Gottenstraeter, 2003; Mederer, 2000). Comparisons of farm accountancy data show that milk yields often vary between farms in a region by a factor of two (Mederer, 2000) and can therefore possibly be considered as a proxy of a farm's efficiency. We extent this reasoning as well to crop and cattle farms. On the other hand, high yields might also reduce the incentives to reduce costs to an absolute minimum or to adopt new technologies, etc. As the regions investigated in the empirical part mainly produce cereals, only the yield of the cereal (i.e., either wheat or maize) that has on average the highest share in total farm cereal output value, is tested for having an impact on the RCD, RTC and RMCD.

Hypothesis 13: Lower output prices contribute to higher rates of (marginal) cost diminution and technical change.
Wieck & Heckelei (2007) test a similar hypothesis, as they expect that lower milk prices contribute to lower marginal variable costs. Their line of reasoning is that the ability of dairies to expand and attract new markets through innovative marketing strategies contributes strongly to the final price for dairy products (Veautheis, 2001) and also to the price for raw milk received by farmers. This contributes to large milk price differentials observed both within the same country and across member states of the EU. It is assumed that these regional price differences also influence regional and marginal cost structures as farms facing lower milk or crop prices are forced to better control their production costs or to cease production (Gardner, 1987). For testing this hypothesis, we use the Törnqvist price indices for outputs (see Paragraph 4.2). Another argument might be that a high price (expectation) might encourage producers to increase production, thereby increasing marginal costs, and hence decreasing the RMCD. However, the implementation of lagged prices would be more suited to represent price expectations (from the part of the producer) and to verify this last argument, which will be discussed later.

Hypothesis 14: Thanks to a catch-up effect, initial inefficient farms will have higher rates of cost diminution and technical change.
Farms that are initially very unproductive compared to the very best performing farms, have a great margin for improvement left. Moreover, they can often achieve high productivity gains by simply copying their more productive neighbors' activities and technologies. Therefore, we could assume that these initially less efficient farms have the possibility to rapidly catch-up and thus exhibit high productivity gains. However, we face the major difficulty within our framework to accurately measure the degree of a farm's inefficiency. As a proxy for this, we propose to take the residuals of our total cost function into account, because a part of these

residuals reflects a farm's inefficiency as it measures the difference between the farm's actual costs and what the farm's costs could have been. Although, we are aware of the fact that many other influencing factors enter into the residual as well and that it is therefore a rather crude approximation to the degree of inefficiency. For instance, the fact of having exceptionally many stones in a field will increase one's cost compared to others. This negative effect will be taken up by the residual, but is therefore not an indicator of inefficiency.

These hypotheses will be tested in section 5 for the crop farms located in the three most important regions for cereal production in the EU, except for hypotheses 6 and 7, which are only applicable to dairy and cattle farms. The validation of these hypotheses will be based on a regression of the RCD, RTC and RMCD on the different determinants, mentioned in the discussion of each hypothesis and Annex 4, as explanatory variables using ordinary least squares (OLS). Therefore, a ln-transformation was performed for both the dependent and independent variables, except for the dummy variables of the different years and subregions. Hence, we retrieve directly the elasticities for the ln-transformed variables. Consequently, the significance of each estimated coefficient can give an indication whether or not this factor has any importance in explaining the estimated values of the RCD, RTC and/or RMCD. Note that we do not control for these variables in the cost function regression, as our objective is to test their impact on the rates of cost diminution and technical change, and not the impact on the cost function itself for each individual farm.

We would like to note as well that alternative versions to hypotheses 12 and 13 could also be considered. These alternatives would search for the impact of past yields and prices and verify the occurrence of some autocorrelation. For instance, one could hypothesize that high past yields attribute to lower current rates of cost diminution and technical change (i.e., a negative lagged effect on RCD and RTC). The underlying suspicion is that high yields in the past might have been obtained as a result of less sustainable agricultural practices (e.g., intensive plowing, massive use of pesticides and inorganic fertilizer, etc.), which boosted agricultural output in the short run. But, there might be a price to pay for these practices in the future, when the soil's nutrients have been completely depleted, the soil structure has been ruined and the fields' biodiversity has collapsed. Hence, we would expect a negative correlation between past yields and current productivity gains. Another alternative hypothesis, related to past prices, is that high past prices might decrease the rate of marginal cost diminution. As theory suggests: we expect farmers to base their production decisions (partially) on past output prices, or in other words, the lagged prices represent the expectation on prices from the part of the producers. When farmers expect prices to decrease, they will decrease their production, and hence their marginal costs. Or in the opposite way: when farmers expect high prices (i.e., a high lagged price index), they will increase production, and hence their marginal costs. Consequently, the RMCD will be limited. This hypothesis, claiming that lower prices contribute to lower marginal costs, was investigated and confirmed by Wieck & Heckelei (2007). Other reasonings might suggest the opposite to happen for the rate of cost diminution and technical change: it is not unlikely to think that farmers will be tempted to increase their production of a particular output, if its price has been high in recent years, thereby seeking after maximal cost minimization and the most optimal technology for producing this particular high-priced output. Moreover, one could also argue that high output prices might induce a bias in technological research and development in the long run, redirecting it towards this particular production (as high returns and profits could be expected here). Hence, more intense research (as a result of high prices) will possibly attribute to higher future RCD and RTC. The problem however for investigating these rather interesting alternative hypotheses is the requirement of disposing of highly-balanced and extensive panel data, as we would need to include lagged variables for several years in order to verify these (long-term) impacts. Unfortunately, because of this reason, our EU-FADN data set is not suited for thoroughly testing these hypotheses, as it is not that highly-balanced (i.e., many farms are only represented for a limited number of years) and the time period covered by the data is not that extensive. Introducing lagged variables (e.g., with a lag of 5 years or more) would therefore result in the loss of many observations.

A very important and final remark we want to address here is the fact that these estimated coefficients merely reflect the possible correlation between the RCD, RTC or RMCD and the different indicators. There is however no information revealed about the direction of the causality between the explicated and explanatory variables. Moreover, careful interpretation of the obtained correlation coefficients is necessary as they reflect not only the impact of the indicators under review, but also other interdependencies between variables that are not formally accounted for by the statistical framework. Expressed differently, these indicators do not keep other uncontrolled variables constant (Wieck & Heckelei, 2007). It should be noted as well that, when testing for the underlying factors attributing to RCD and RTC for cattle and dairy farms, one should never test hypothesis 6 and 7 simultaneously, due to an expected multicollinearity issue appearing between the explanatory variables ‘stocking density’ and ‘grassland ratio’ in the regression.

4. Data

4.1. The EU-Farm Accountancy Data Network

During the empirical part of this study, we make use of data obtained by the EU-FADN. According to the European Commission or EC (2010), the FADN is an instrument for evaluating the income of agricultural holdings and the impacts of the Common Agricultural Policy. The concept of the FADN was launched in 1965 and currently consists of an annual survey carried out by the Member States of the EU. The EU services responsible for the operation of the FADN collect every year accountancy data from a sample of the agricultural holdings in the different Member States. Derived from national surveys, the FADN is the only source of microeconomic data that is harmonised, i.e., the bookkeeping principles are the same in all countries. Holdings are selected to take part in the survey on the basis of sampling plans established at the level of each region in the EU. The survey does not cover all the agricultural holdings, but only those which due to their size could be considered commercial. So, note that not all farms are represented by the data, as there is a certain threshold for the farm's size in order to be taken into account in the survey. Therefore, a group of small farms might be badly represented by the data. Furthermore, the methodology applied aims to provide representative data along three dimensions: region, economic size and type of farming.

Moreover, the objective of the network is to gather accountancy data from farms for the determination of incomes and business analysis of agricultural holdings. Currently, the annual sample covers approximately 80 000 holdings. They represent a population of about 5 000 000 farms in the EU, which covers approximately 90% of the TUAA and accounts for about 90% of the total agricultural production. The information collected for each sample farm, concerns approximately 1 000 variables referring to physical and structural data, such as location, crop areas, livestock numbers, labour force, etc., as well as economic and financial data, such as the value of production of the different crops, stocks, sales and purchases, production costs, assets, liabilities, production quotas and subsidies, including those connected with the application of the CAP measures, etc.

During this work, we disposed of EU-FADN panel data including several Member States for the period 1989 – 2011[6] for econometric estimation. In order to use this panel, we had to overcome the difficulty of merging data following different classification systems: data for the years ranging from 1989 until 2009 were constructed using standard gross margins (SGM) to classify agricultural holdings by type of farming and by economic size, whereas data of the subsequent years were classified according to standard output (SO). According to Eurostat (2017 b), the SGM is a measure of the production or the business size of an agricultural holding. It is based on the separate activities or 'enterprises' of a farm and their relative contribution to overall revenue. For each separate activity (for instance wheat, dairy cows or a vineyard), a SGM is estimated, based on the area (for crop output) or the number of heads (for animal output) and a standardized SGM coefficient for each type of crop and livestock,

[6] Additional EU-FADN data for the years 2012 and 2013 was requested and received. However, due to several issues and a lack of time, we were not yet able to implement this data for our econometric analysis. First, we had to overcome a mismatch between the farm identifier variables in the new datasets and the initial datasets (in which we have succeeded). Another issue is the fact that with the additional years of FADN data, several external indices derived from Eurostat need to be updated as well, in order to obtain valid estimations for these additional years. However, while importing this additional data, we encountered several problems due to, for instance, changing baseyears for these indices, incompatibility with the existing Stata codes, etc.

calculated separately for different geographical areas to allow for differences in profit. The sum of all these margins per hectare of crop and per head of livestock in a farm is a measure of its overall economic size, expressed in European size units (ESU). Hence, SGM represent the level of profit to be expected on the average farm under 'normal' conditions (discounting, for example, disease outbreaks, fires and floods, adverse weather, etc.). The SGM for a farm is the difference between the gross production (to which subsidies are added) and the variable specific costs. Furthermore, SGM enables to classify farms in different types of farming, based on the share of each separate activity in the total SGM of a farm as defined by the legislation. For instance, if the share of olive trees in the total SGM is over 2/3, the farm is taken as specialist olives.

However, from 2007 and onwards, the EU-FADN started using the SO classification as an alternative to the SGM. The SO of an agricultural product (crop or livestock) is the monetary value of the agricultural output at farm-gate price, in euro per ha or per head of livestock. There is a regional SO coefficient for each product, as an average value over a reference period of 5 years (by default). The sum of all the SO per hectare of crop and per head of livestock in a farm is a measure of its overall economic size. Note that the unit used to measure SO is the euro and not ESU (= 1.200 euro) as in the SGM classification.

Thus, the principle of both concepts SGM and SO is the same; only the way they are calculated differs:

- $SGM = Output + Direct\ Payments - Costs$
- $SO = Output$

The decision to leave SGM was driven by the CAP moving from coupled to decoupled payments. Since decoupled direct payments cannot be attributed to any specific production, they were excluded from the calculation. If the costs were kept in the calculation, there would be the possibility of negative SGM values in cases where costs were higher than the output. Therefore, only the output is taken into account for the SO classification. In light of our work, the use of different classification systems means we have to specify different definitions of the type of farms (crop, dairy or cattle) according to the classification system (SGM or SO).

In what follows, we will discuss the two-step procedure for preparing this data for the econometric estimation. First, every variable and its price is generated at the disaggregated level in the 'data preparation' step. This is done for variable inputs, quasi-fixed inputs and outputs for the medium- and long-term specifications by country. Missing prices and other indices are imputed using data from Eurostat. Second, depending on the choice of farm type and time specification, the dataset is more precisely shaped in order to have only the relevant and needed data left for further estimations. In this 'data aggregation' step, variables are aggregated according to a predetermined aggregation scheme (see further). This results in a dataset containing then both aggregated and disaggregated input and output values (*'X'*, respectively *'Y'*), input and output prices (*'W'*, respectively *'P'*) and input and output quantities (*'x'*, respectively *'y'*), which can consequently be used for the estimation of the cost function and its resulting farm-performance indicators (third step). In the final stage, we examine the factors underlying the estimated rates of cost diminution and technical change. This routine, as organized in Stata, is illustrated by Figure 8.

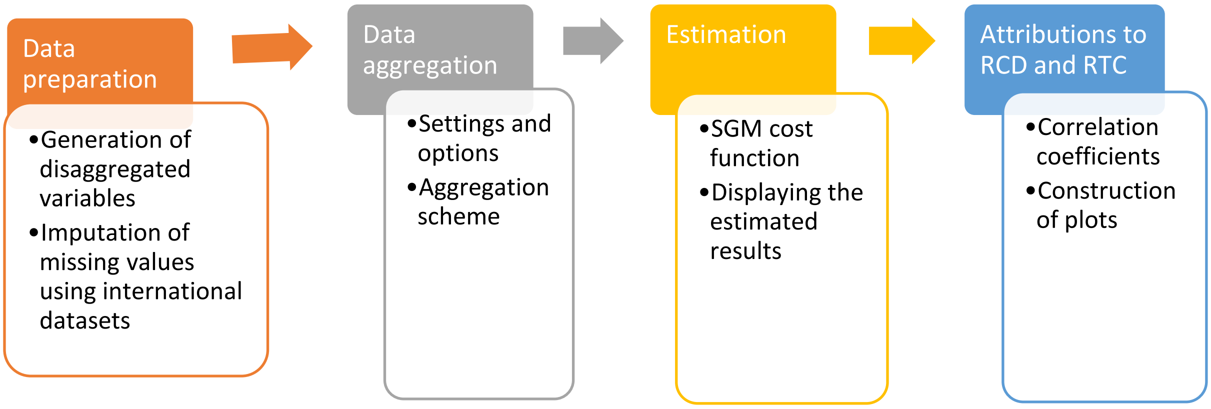

Figure 8. Schematic view of the Stata routine.
Source: adapted from Henry de Frahan et al., 2015.

To end this paragraph, we would like to mention the fact that we rescaled several variables in order to ensure numerical stability. Therefore, output quantities and quasi-fixed input quantities are rescaled such that their mean squared error lies between 1 and 10. For example, y_m is transformed into

$$y_m^{(s)} = y_m . s_m$$

$$s_m = 10^{\left(-\,int\left[\log_{10}\sqrt{E_{[y_m]^2}+Var_{[y_m]}}\right]\right)},$$

where $int[.]$ denotes the nearest integer. For more information on the rescaling of the output and quasi-fixed input quantities, we refer to Henry de Frahan et al. (2015).

4.2. Törnqvist index construction

As discussed in the MIMO Deliverable 8 (Henry de Frahan et al., 2015), Törnqvist price indices are constructed at the regional level, since farm-level aggregate price indices proved too erratic. The Törnqvist price indices are expressed with respect to base year $t_0 = 2005$. Supposing all inputs $h = 1, \dots, \sum_{i=1}^{I} N_i$ are grouped into $i = 1, \dots, I$ categories, the Törnqvist index w_{irt} is defined for each input aggregate *i*, each geographical unit *r* and each period *t* as

$$w_{irt} = \prod_{j=1}^{N_i}\left(\frac{w_{jrt}}{w_{jrt_0}}\right)^{\frac{g_{jrt}+g_{jrt_0}}{2}}$$

$$g_{jrt} = \frac{V_{jrt}}{\sum_{k=1}^{N_i} V_{krt}},$$

where N_i denotes the number of input-components encompassed by the aggregate input *i*, w_{jrt} represents the average of farm-gate prices of input-component *j* in geographical unit *r* in period *t*, and V_{jrt} represents the total value spent on input *j* in geographical unit *r* in period *t*.

Farm-gate prices w_{jft} for each input-component *j* at time *t* for farm *f* are obtained by dividing the value of total purchases of the farm (V_{jft}) by the farm-total volume purchased (N_{jft}). An average regional price of input *j* in region $r = 1, \dots, R$ in period *t* is estimated by dividing total purchases within region *r*: $V_{jrt} = \sum_{f=1}^{F_r} V_{jft}$ by total volume purchased $N_{jrt} = \sum_{f=1}^{F_r} N_{jft}$. A country-wide price average is obtained similarly, and, if needed, country-wide average prices are also provided by Eurostat (see Paragraph 4.3).

Similarly, the Törnqvist index τ_{mrt} for output aggregate *m* in geographical unit *r* in period *t* is given by

$$\tau_{mrt} = \prod_{n=1}^{N_m} \left(\frac{p_{nrt}}{p_{nrt_0}} \right)^{\frac{g_{nrt}+g_{nrt_0}}{2}}$$

$$g_{nrt} = \frac{V_{nrt}}{\sum_{o=1}^{N_o} V_{ort}},$$

where N_m denotes the number of output-components *n* encompassed by the output aggregate m, p_{nrt} represents the average farm-gate price of output-component *n* produced in geographical unit *r* in period *t*, and V_{nrt} represents the total revenue generated by output-component *n* in geographical unit *r* in period *t*. Average regional and national prices of product *n* in period *t* are again obtained by dividing the value of total production by total number of units sold. Paragraph 4.3 explains how farm-gate output prices are imputed when missing.

A final remark we would like to make is the way extreme farm-gate prices of inputs and outputs are removed for the calculations of average regional or country prices of inputs and outputs. Farm-gate prices that have a probability of occurrence that is smaller than one over twice the sample size are disregarded from that calculation. For input prices, extreme values of w_{jrt} are defined as

$$\left|(w_{jft} - w_{jrt})\right| > \Phi^{-1}\left(1 - {}^{1}\!/_{2F_r}\right) * SD_{w_{jft}},$$

where Φ^{-1} denotes the inverse cumulative normal distribution function, F_r the sample size, w_{jrt} the regional or country average of w_{jft}, and $SD_{w_{jft}}$ the standard deviation of w_{jft}. Extreme values for output prices p_{nrt} are calculated and removed in a similar way (see Henry de Frahan et al., 2015).

To preserve the relationship

$$\tau_{mft} = \frac{p_{mft}}{p_{mft;b}},$$

we use the following definitions for prices of aggregates

$$p_{mft} = \prod_{n=1}^{N_m} (p_{nft})^{\frac{g_{nft}+g_{nft_0}}{2}}$$

$$p_{mft;b} = \prod_{n=1}^{N_m} (p_{nft_0})^{\frac{g_{nft}+g_{nft_0}}{2}}.$$

The price in the base year of an aggregate, $p_{mft;b}$, can thus vary from year to year, depending on the varying exponent ${(g_{nft} + g_{nft_0})}/{2}$.

4.3. Imputation of missing prices

Output prices p_{nft} are in general computed from sale values and volumes in the EU-FADN database, if not from production values and volumes (see previous paragraph). If the necessary information is missing, it is supplemented with prices from Eurostat. Information on input prices w_{jft} is mainly obtained from Eurostat, although for some inputs it also stems from the EU-FADN database. For further details and the procedure by which these prices are imputed, we refer to the MIMO Deliverable 8 (Henry de Frahan et al., 2015).

4.4. Data preparation

As previously discussed, to prepare the data for the econometric estimation, we apply a two-step procedure. The first step consists of pre-processing the data in order to have the EU-FADN datasets ready for further manipulations. This routine consists in constructing every needed variable and the imputation of missing data as previously discussed. At the end of this routine, a complete dataset including all input and output values and related prices and interest rates is stored in a data file, which will be used in the following section.

4.5. Data aggregation

A general remark we would like to make first is that, because of limitations in degrees of freedom, risk of multicollinearity and failure to converge, the specification of the cost function includes only a limited number of variable input categories, a limited number of output categories and a limited number of quasi-fixed input categories by farm type. We note here the importance of our separability assumption when aggregating data (i.e., producing one output belonging to a broad output category cannot directly affect producing another output that belongs to another broad output category).

In this data aggregation section of the Stata routine, following the user's choices including farm type, time horizon and possibly the subregion, the dataset is more precisely shaped in order to have only the relevant and needed data left for further estimations. Moreover, the aggregation scheme for fixed inputs, variable inputs and outputs is determined during this procedure. The farm type choice allows to select the most relevant farms in the dataset (i.e., crop, dairy or cattle farms), while the choice between the medium- and long-term specifications has an influence on the input aggregation scheme. For the detailed aggregation schemes adopted for the estimation, we refer to the MIMO Deliverable 8 (Henry de Frahan et al., 2015). In light of this work, we only report how the most aggregated variables are constructed by the figures depicted in Annex 5, which respectively show the aggregation schemes adopted for fixed inputs for the medium- and long-term specifications, variable inputs for the medium- and the long-term specification and outputs for sale.

As reported by Annex 5.1, for the medium-term, we consider three inputs as being fixed: i.e., agricultural area, non-land capital and unpaid labour input, while, for the long-term, we only consider one fixed input, namely unpaid labour input. Accordingly, for the long-term time horizon, agricultural area and non-land capital become variable inputs. As an important reminder, we would like to stress again that a fixed input is does not necessarily mean it is constant over time, but it is just an input that is not (less) responsive to price variations.

Note carefully that there is no need to single out explicitly on-farm forage crops that are used to feed on-farm animals. Inputs to produce those on-farm forage crops are already counted in the different input categories. On-farm forage crops that are used to feed on-farm animals and, hence, not for sale are intermediate farm inputs. Note in parallel that outputs are only those sold outside the farm. There is no need then to figure out how much inputs are used to grow those on-farm forage crops and how much on-farm crops are produced. Note finally that animal products are denominated in terms of either live animals or dairy products since farms sell those products, nothing else. At the end of this routine, a data set with only the needed variables for estimations is generated, accounting for the chosen type of farm, the time specification and the resulting aggregation scheme.

In the MIMO Deliverable 8 (Henry de Frahan et al., 2015), the authors describe in detail how input and output data are prepared according to the default aggregation schemes, including the corresponding variable names as present in the EU-FADN and Eurostat dataset. They also discuss the rental rate, interest rate and opportunity cost of land and the stock, depreciation rate, interest rate and opportunity cost of non-land capital. Hence, for further details, we refer once again to this work.

4.6. Estimation

The last section of the Stata routine takes care of estimations. The user is able to choose estimation options such as the constraints to impose on the coefficients of the cost and input demand function, in order to make it theoretically consistent. Further specific details, specifications and properties of the actual estimation procedure we perform, will be discussed in section 5.

4.7. Introduction of investigated regions

4.7.1. General introduction

During the empirical part of this work, in which we attempt to demonstrate the capabilities of the framework developed in section 3, we are mainly interested in examining the productivity gains realized by crop farms. Therefore, we decided to run the estimations for crop farms located in the three most important NUTS 1 regions for cereal production in the EU, and, at the same time, the regions that were acceptably represented in the EU-FADN dataset. By decreasing order of production importance, they can be ranked as the Paris Basin or Central France (coded as ‘FR2’), West France (coded as ‘FR5’) and Central Spain (coded as ‘ES4’). As introduced previously, we will examine the productivity gains realized by these three regions during the period 1989 – 2011. The following paragraphs will be dedicated to a brief description and a summary of several characteristics of these regions.

4.7.2. Regional characteristics

4.7.2.1. Central France (FR2)

This region is also known as the "Paris Basin". According to the International Standard for country codes 'ISO3166' of the International Organization for Standardization (1997) or ISO, there are nine different NUTS 1 statistical regions in France, which are defined according to the '*Zones d'études et d'aménagement du territoire*' ('Research and National Development Zones') or ZEAT and the '*Départements d'outre-mer*' ('overseas departments') or DOM. Annex 6 represents a map of France with the green area indicating the Central France, a.k.a., Paris Basin (or '*Bassin parisien*') NUTS 1 region. Hence, at the NUTS 2 level, this region consists of the Champagne-Ardenne, Picardy, Upper Normandy, Centre-Val de Loire, Lower Normandy and Burgundy. Together, they occupy an area of 145 645 km².

4.7.2.2. West France (FR5)

The NUTS 1 region known as West France, or FR5, can be decomposed in three NUTS 2 regions, i.e., Pays de la Loire, Brittany and Poitou-Charentes, and is indicated in pink in Annex 6. The total area of this region equals 85 099 km² (Czech Statistical Office, 2005).

The importance of both Central and West France for the country's crop production is illustrated by Annex 7, which represents the density of the major field crops grown in France. These field crops include cereals such as wheat, barley, triticale or corn; oilseeds such as rapeseed and sunflower; and protein crops such as peas, beans and lupins.

4.7.2.3. Central Spain (ES4)

In Spain, the NUTS 1 regions consist of groups of autonomous communities (Eurostat, 2011). More specifically for Central Spain (ES4), this region consists of Castile-Leon, Castile-La Mancha and Extremadura, which is represented by the pink area in Annex 8. The total area of this region equals 215 320 km², and is therefore comparable to the size of both French regions combined. Similar as for France, the spatial distribution of the different cereal productions in Spain is depicted in Annex 9.

4.7.2.4. Regional comparison

When comparing farm structures between France and Spain, it is important to note that, on average, the area per holding in Spain equalled 24.0 ha and 55.0 ha for those in France. Also, in 2010, the UAA per inhabitant was equal to 0.52 ha/person in Spain and 0.43 ha/person in France (Eurostat, 2012). To give further insights in how these three regions compare to each other, we summarize several indicators on farm structure and local agricultural production at the NUTS 2 level in Table 4 for the year as reported by Eurostat (2017, a).

Based on these statistics, we can conclude that the French farms show similar characteristics for both NUTS 1 regions. The agricultural sector in Central-Spain on the other hand, is characterised by more but relatively smaller farms, mainly in terms of economic size. The cereal production in Spain also seems to be more diversified when compared to France (the latter being highly specialised in the production of common wheat and spelt).

Table 4. Economic indicators on farm structure and local agricultural production for Central France, West France and Central Spain at the NUTS 2 level.

NUTS 1	*NUTS 2*		*Number of agricultural holdings, 2010 (thousand holdings)*	*Average size of farms, 2010 (hectares of UAA per agricultural holding)*	*Average economic size of farm holdings, 2013 (thousand EUR)*	*Harvested production of cereals (including seed), 2015 (tonnes per hectare of TUAA)*	*Most commonly grown cereal (relative to EU-28 average)*
Central France (FR2)	FR21	Champagne-Ardenne	24.6	62.5	196.2	4.1	Common wheat and spelt
	FR22	Picardy	13.9	95.8	201.0	4.9	
	FR23	Upper Normandy	11.5	67.4	144.0	4.0	
	FR24	Centre	25.1	92.2	152.7	3.9	
	FR25	Lower Normandy	23.9	50.6	108.4	1.9	
	FR26	Burgundy	20.3	86.7	151.9	2.2	
West France (FR5)	FR51	Pays de la Loire	34.4	61.2	181.2	2.3	Common wheat and spelt
	FR52	Brittany	34.5	47.6	205.4	2.5	
	FR53	Poitou-Charentes	25.5	67.6	134.8	3.2	
Central Spain (ES4)	ES41	Castile-Leon	98.3	54.6	49.7	1.3	Common wheat and spelt
	ES42	Castile-La Mancha	122.4	33.4	27.7	0.8	Barley
	ES43	Extremadura	65.2	39.6	32.9	0.6	Grain maize and corn-cob-mix

Source: (Eurostat, 2017 a)

4.7.3. Regional descriptive statistics

In what follows, we will summarize and discuss some of the most relevant descriptive statistics derived from our EU-FADN datasets concerning this region. For instance, the number of observations present in the datasets for each year and region can be found in Annex 10. In the EU-FADN dataset, a weight is attached to each observation, indicating the number of similar farms that are represented by this single observation. In other words, each farm recorded in the dataset represents several similar farms within this region. Hence, by weighting the observations, we get a far more extensive, accurate and representative dataset: for example, by weighting the observations, the estimations for the regions of Central France will be based upon 858 061 observations, instead of 'only' 19 063 observations (originally present in the dataset). Hence, we will indicate each time whether it concerns weighted or unweighted statistics when reporting them. A summary of the most relevant weighted descriptive statistics for the variables for each region derived from our dataset is given in Annex 11. We adopt the aggregation scheme for the long-term specification of crop farms as described by section 4.5. Hence, these descriptive statistics rely on the datasets obtained after the second step (data aggregation) of the Stata procedure (see section 4.1). Note as well that the output variables and fixed input variable are rescaled, as mentioned in section 4.1. Annex 11 also reports several negative output values, which might be explained by stock variations from year to year. However, these negative values are not taken into account for the actual estimation.

Note that the dataset for the region of Central Spain includes by far the most observations, i.e., even more observations than the other two regions combined. We notice as well that many more small farms are included in the sample of Central Spain, when looking at the average observed cost. These findings were already noted in Table 5 with the data of Eurostat.

Hence, we have a modest indication that our samples' contents truly represent the agricultural crop sector for these regions. Unfortunately however, the sample size for West France is relatively small.

The weighted descriptive statistics concerning the investigated factors possibly attributing to the rates of cost diminution and technical change (cf. Paragraph 3.4.2) for the crop farms in the different regions are included in Table 5. Observations with negative output values are *ex-ante* removed here. As a reminder, we summarize how these indicators related to these crop farms (orientated to cereal production) are defined once again: the indicator of the farm's *size* is the TUAA (in ha), the *degree of specialization* is the share of cereal output value in a farm's total output value, *capital per AWU* (i.e., annual work unit) and *capital per size* are the ratios of the yearly value of non-land assets contributing to production and the total labour input or the TUAA respectively, the *land ownership ratio* is the ratio of the OUAA and the TUAA, the *subsidy ratio* is the ratio of total subsidies a farm receives and its total costs, the *intensity of crop production* is the ratio of crop-specific inputs (seeds, fertilizers, pesticides, etc.) over total input, *yields* obviously denotes the yields of wheat production (i.e., the most important cereal on average; in 100 kg / ha), and finally the *Törnqvist price* index speaks for itself.

Table 5. weighted descriptive statistics of the factors possibly attributing to the RCD and RTC.

Central France (FR2)				
Variable	Mean	SD	Minimum	Maximum
Size	122.11	71.30	5.80	668.24
Degree of specialization	0.60	0.19	0.00	1.00
Capital per AWU	56 898.83	41 680.06	0.00	461 964.80
Capital per size	708.79	515.88	0.00	8 173.69
Land ownership ratio	0.17	0.23	0.00	1.00
Subsidy ratio	0.25	0.15	0.00	1.01
Intensity of crop prod.	0.25	0.07	0.01	0.56
Yields of wheat production	73.61	17.16	0.00	141.45
Törnqvist price index	1.40	0.29	1.00	1.96
TC residual	-550.85	23 427.94	-253 629.20	266 773,50
West France (FR5)				
Variable	Mean	SD	Minimum	Maximum
Size	85.23	63.20	1.54	795.49
Degree of specialization	0.65	0.24	0.00	1.00
Capital per AWU	36 253.34	30 960.10	84.93	269 685.80
Capital per size	773.67	1 720.60	0.98	38 202.49
Land ownership ratio	0.29	0.30	0.00	1.00
Subsidy ratio	0.28	0.16	0.00	1.05
Intensity of crop prod.	0.23	0.08	0.01	0.55
Yields of wheat production	54.86	23.05	0.00	131.67
Törnqvist price index	1.34	0.28	0.97	1.86
TC residual	-863.39	15 885.46	-92 499.89	112 049.00
Central Spain (ES4)				
Variable	Mean	SD	Minimum	Maximum
Size	61.19	74.11	0.00	3 065.00
Degree of specialization	0.74	0.31	0.00	1.00
Capital per AWU	16 310.46	21 938.55	0.00	404 480.60
Capital per size	321.42	405.49	0.00	6 266.56
Land ownership ratio	0.72	0.37	0.00	1.00
Subsidy ratio	0.27	0.22	0.00	5.63
Intensity of crop prod.	0.18	0.08	0.00	0.67
Yields of wheat production	10.98	16.13	0.00	89.98
Törnqvist price index	1.13	0.17	0.92	1.42
TC residual	-27.02	8 606.55	-70 541.16	79 515.49

5. Selected estimation results

5.1. Estimation procedure

5.1.1. Estimation program

The following sections will report the actual estimation results obtained by applying our Stata procedure to the datasets of the three regions introduced in Paragraph 4.7. But first, we pay some more attention to the specific estimation procedure applied during the Stata routine. Our estimation uses the long-term specification of the aggregation scheme presented in Paragraph 4.5. Hence, we only consider unpaid labour as a quasi-fixed input. The system of input demands (Eq. 23) is estimated by a fixed effect non-linear seemingly unrelated regression (NLSUR). The NLSUR program coded in Stata fits the system of nonlinear input demand equations by feasible generalized nonlinear least squares (FGNLS), which is discussed in the following paragraph. In order to obtain a fixed effect regression (which can optionally be requested in the Stata program), a within-transformation is performed (i.e., we subtract the farm-specific temporal mean of each variable included in the model). In doing so, we purge our model from a possible omitted variable bias induced by the unobserved factors that are constant over time and related to each specific farm. In other words, we rule out the effects that are proper to each farm and that contribute to the level of productivity of a particular farm. After estimation, these farm-specific effects can be retrieved (by subtracting the farm-specific average predicted input demand or cost from the farm-specific average observed input demand or cost) and included in the prediction of a farm's specific input demand or costs. Hence, after estimation, we predict the farm-specific fixed effect for farm *f* on the input demand of input *j* as

$$FE_{x_{j},f} = \overline{x_{J,f}} - \overline{x_{J,f,ID}}\ ,$$

where $\overline{x_{J,f}}$ represents the average observed input demand for input *j* of farm f and $\overline{x_{J,f,ID}}$ represents the average predicted input demand for input *j* of farm *f*. Consequently, the input demand for input *j* of a farm *f* at time *t* can be predicted more precisely by including this fixed effect as follows:

$$x_j FE_{f,t,ID} = x_{j,f,t,ID} + FE_{x_j,f}\ ,$$

where $x_{j,f,t,ID}$ represents the predicted input demand for input *j* of farm *f* at time *t* (based on the coefficients obtained by the estimation program). The total cost (including its fixed effect) of a farm f at time t, $TCFE_{f,t}$, is computed in a similar way: the fixed effect for the *TC* of a particular farm *f* is defined as

$$FEcost_f = \overline{Cost_f} - \overline{Cost_{f,ID}}\ ,$$

where $\overline{Cost_f}$ denotes the average observed *TC* of farm f and $\overline{Cost_{f,ID}}$ denotes the average predicted *TC* of farm *f*. Consequently, this fixed effect is used to predict a farm's *TC* at a particular time *t* more precisely:

$$TCFE_{f,t} = Cost_{f,t,ID} + FEcost_f\ , \qquad \text{(Eq. 24)}$$

where $Cost_{f,t,ID}$ denotes the predicted *TC* for farm *f* at time *t*.

Note that a fixed-effect model is only used for the estimation of the input demand equations and not for the regression of the rates of cost diminution, technical change and marginal cost diminution on the different explanatory variables to test our different hypotheses (cf. Paragraph 3.4.2). A fixed-effect regression would not allow to test the impact of explanatory variables that are constant over time, on the RCD, RTC and RMCD. Hence, we would not have been able to estimate, for example, the correlation coefficients for the different subregions in which farms are located, for the land ownership ratio and for the size of farms (as these are likely to stay relatively constant over time as well).

The use of a NLSUR program in Stata allows to specify the type of standard error reported, which includes, among others, either standard errors that are robust to some kinds of misspecification, or standard errors that allow for intragroup correlation by clustering the observations (by years of observation, for example). After estimation of the different input demand equations, we notice that the presence of heteroscedasticity is not unlikely, as the variance of the residuals seems to increase with higher levels of (predicted) input demands. Therefore, we first verify whether there is a need or not to cluster the observations by year. Clustering would allow for intragroup correlation, i.e., the observations are independent across groups (clusters), but not necessarily within groups. If there is no need for clustering, the heteroscedasticity problem can simply (and efficaciously) be remedied by using robust standard errors. To verify the need of clustering the observations, we plot the squared residuals and the mean of the squared residuals over the different years for the different inputs. Consequently, no obvious pattern can be detected in these plots and we therefore decide to use the option of robust standard errors, because there seems to be no need to cluster the observations by year. In doing so, the possible occurrence of heteroscedasticity does not obstruct the estimations and findings. All these different plots related to the residuals can be found in Annex 12. Note that this choice does only affect the estimated standard errors of the coefficients, not the estimated coefficients themselves.

We would like to note also that only observed input demands that are strictly positive are used to estimate the system of input demands, since zero input demands represent a corner solution of the farm’s cost minimization problem. Consequently, Shephard’s lemma does not hold and demand equations with input demands that are not strictly positive are dropped from the system of equations for that particular farm. Also, when estimated coefficients have both an infinite standard error and a value identical to its initial value, then these coefficients can be successively and automatically set to zero in an iterative process. The first estimated coefficient that appears in the list to have these two features, is first set to zero. The system of input demands is then estimated. The next first estimated coefficient that appears in the list to have these two features, is set to zero. The system of input demands is then estimated. This process is repeated until no estimated coefficient has these two features in the list. Then, if there are still coefficients with an infinite standard error, the first estimated coefficient that appears in the list to have an infinite standard error, is set to zero. The system of input demands is then estimated again. The next first estimated coefficient that appears in the list to have an infinite standard error, is set to zero. The system of input demands is then estimated again. This process is repeated until no estimated coefficient has an infinite standard error in the list. A final remark we would like to make is that throughout this work, we impose a significance level of 5%.

5.1.2. Feasible generalized nonlinear least squares

For the estimation of the system of nonlinear input demand equations, a NLSUR command is used in Stata, which fits the system of nonlinear equations by FGNLS. This concept can be viewed as a nonlinear variant of Zellner's seemingly unrelated regression model (Zellner, 1962; Zellner & Huang, 1962; Zellner, 1963) and is therefore commonly called nonlinear SUR or nonlinear SURE. Formally, the model fit by a NLSUR is

$$\begin{aligned} y_{i1} &= f_1(x_i, \beta) + u_{i1} \\ y_{i2} &= f_2(x_i, \beta) + u_{i2} \\ \vdots &= \quad \vdots \\ y_{iM} &= f_M(x_i, \beta) + u_{iM} \end{aligned}$$

for $i = 1, \dots, N$ observations and $m = 1, \dots, M$ equations. The errors of the *i*-th observation, $u_{i1}, u_{i2}, \dots, u_{iM}$, may be correlated, so fitting the *m* equations jointly may lead to more efficient estimates. Moreover, fitting the equations jointly allows us to impose cross-equation restrictions on the parameters. Not all elements of the parameter vector β and data vector x_i must appear in all the equations, though each element of β must appear in at least one equation for β to be identified (StataCorp, 2017 b). The FGNLS method was introduced by Zellner (1962), who claims that, under conditions generally encountered in practice, it is found that the regression coefficient estimators thus obtained are at least asymptotically more efficient than those obtained by an equation-by-equation application of least squares and are considered as best linear unbiased estimators (BLUE). In this two-step procedure, regression coefficients in all equations are estimated simultaneously by applying generalized least-squares, as proposed by Aitken (1936) to the whole system of equations. To construct such estimators, they employ estimates of the disturbance terms' variances and covariances based on the residuals derived from an equation-by-equation application of least squares.

5.1.3. Imposed restrictions

This part is dedicated to the different imposable conditions as discussed in Paragraph 3.3. Firstly, the symmetry and adding up restrictions are always imposed (cf. Paragraph 3.3.3). Consequently, we decided to impose all curvature conditions of a theoretically consistent cost function (cf. Paragraph 3.3.5). These include the negative semi-definiteness of matrix E (to ensure concavity of *TC* in input prices), the positive semi-definiteness of matrix F (to ensure convexity of *TC* in quasi-fixed inputs) and the positive semi-definiteness of matrix G (to ensure convexity of *TC* in output quantities). Following the previously discussed recommendations concerning the simultaneous imposition of monotonicity and curvature conditions, we do *not* impose the monotonicity condition for input prices (i.e., the non-negativity of the input demands to ensure the *TC* function to be non-decreasing in input prices) and the monotonicity condition for quasi-fixed inputs (i.e., a monotone decreasing *TC* function with respect to fixed inputs). However, we do impose the non-negativity condition of the marginal costs to ensure the *TC* function to be non-decreasing in output quantities (cf. Paragraph 3.3.4). Because we cannot impose all restrictions *ex-ante*, we will dedicate some attention *ex-post* to check whether or not these conditions are fulfilled.

5.1.4. Outlier removal procedures

In order to further improve the framework developed by De Blander et al. (2011) and Henry de Frahan et al. (2015), we introduce a procedure to remove outliers *ex-ante* by applying the

Chauvenet's criterion (Taylor, 1997). Therefore, outliers are identified after a first estimation procedure. The observations that have been identified as an outlier, are then removed and consequently, we initiate a new loop to re-estimate the coefficients of the input demand equations (without these outliers) on which the rest of the analysis will be based.

During the identification process of outliers, the standardized residual of the total cost of a farm in a particular year is compared to a cut-off value, μ. The (ordinary) residuals of a farm's total cost are obtained by regressing the observed *TC* (indicated as "$Cost_{f,t}$") on the predicted *TC*, indicated as "$TCFE_{f,t}$". The latter is calculated after the estimation of the system of input demand equations and includes the farms' fixed effects (cf. Eq. 24). Consequently, these residuals are standardized by dividing them by their standard deviation, $SD_{res_{TC}}$. Now, observations with a standardized residual (in absolute value) that has a probability of occurrence that is smaller than one over twice the sample size are disregarded from that calculation. Hence, the cut-off value, μ, is defined as

$$\mu = \Phi^{-1}\left(1 - {}^{1}/_{2\mathrm{N}}\right)$$

where Φ^{-1} denotes the inverse cumulative normal distribution function and *N* the number of observations. If the absolute value of the standardized residuals is greater than this cut-off value μ, the observation is identified as an outlier and thus removed. Hence, we obtain the following condition for an observation to be identified as an outlier

$$\left|res_{TC,f,t}\right| > \Phi^{-1}\left(1 - {}^{1}/_{2\mathrm{N}}\right) * SD_{res_{TCFE}},$$

with $res_{TC,f,t}$ denoting the (ordinary) residual of the *TC* for a certain observation of a farm *f* at a particular time *t*. As discussed before, after all outliers have been removed, the estimation procedure is reinitiated using the remaining data. It is possible that after the second estimation procedure, again some observations can be identified as an outlier, based on the new estimates. However, according to Taylor (1997), agreement seems widespread that Chauvenet's criterion should not be applied a second time using the recalculated values of the estimators. It should be noted as well that for several indicators (i.e., the ORTS, PSRTS, ESCP, RMCD, RCD, RTC and FBTC) outliers are removed for the reported statistics, based on Chauvenet's criterion.

5.2. Validation of the model

Now that we have introduced and discussed the different principles according to which our estimation is performed, we will report the results as obtained by the Stata routine for the three different regions in the following paragraphs. A summary of all the estimated coefficients (including their standard deviations, significance, etc) for each region can be found in Annex 13. Table 6 indicates the number of coefficients that turn out to be significant, and the number of observations removed after being identified as an outlier, together with their share in the total number of coefficients or observations. Based on this table, we conclude that an acceptable number of observations was rejected (as being outliers) after the first estimation loop, and that their shares are located within the same range for each region. The number of significant parameters is also acceptable for every region. Note that this number is clearly not related to the size of the sample, as the database for West France included by far the least observations. We note as well that after this final loop, again 103, 37 and 217 observations could be identified as *TC* outliers based on Chauvenet's criterion for the regions of Central France, West France and Central Spain respectively. However, they were not removed from the data (cf. Paragraph 5.1.4).

Table 6. Number of significant parameters and number of observations removed after outlier identification and their shares in the total number of parameters or observations.

	Central France	**West France**	**Central Spain**
Number of significant parameters (out of 73) [(1)]	62 *(84.9%)*	57 *(78.1%)*	47 *(64.4%)*
Number of outliers removed	272 *(1.4%)*	83 *(2.4%)*	340 *(1.4%)*

(1) At the 5% significance level

Another important aspect for the validation of the model is to verify whether the monotonicity conditions that could not be imposed *ex-ante*, are fulfilled. The first condition of a well-behaved cost function we need to verify *ex-post* is that the estimated cost function is non-decreasing in input prices, which implies that all input demands should be positive (cf. Paragraph 3.3.4). We therefore generate summary tables for the weighted input demands (in euro value at base-year prices) and verify whether the number of negative observations is limited. These tables can be found in Annex 14. In general, this condition is fulfilled for most input demands in most years, in particular Central France exhibits excellent results for this condition. On the other hand, the condition is most violated for the non-land capital input category, especially in Central Spain. Note that, when looking at the crop-specific inputs, this condition is very well fulfilled, with a maximum of only 0.17% of the (predicted) crop-specific input demands on average that are negative across the three regions.

The second monotonicity condition that should be verified *ex-post* is the non-increase of the cost function in fixed inputs. Therefore, we report the summary tables of the derivatives of the weighted total costs with respect to fixed inputs in Annex 15. For our cost function to be well-behaved and theoretically consistent, we should obtain high rates of negative values this time. With a percentage of 82.77% and 99.74% of negative marginal costs with respect to fixed inputs on average for Central-Spain and West-France respectively, we are quite pleased to report this condition is (partially) fulfilled for these regions. However, we obtain disappointing results for Central France with on average only 6.07% of negative marginal costs (w.r.t. fixed input), which are mainly observed for the first year. It remains unclear to us why we obtain such a considerable violation of this condition for this particular region, especially when we consider that during the first estimation loop, we obtained a very satisfying indication with a negative value in no less than 99.27% of the cases. This means that by removing only 272 observations (out of 19 063), somehow this condition is suddenly strongly violated. Unfortunately, due to time limits, this could not be further investigated.

Note that it is possible in Stata to easily check as well whether the *ex-ante* imposed curvature conditions are actually met by reporting the eigenvalues of matrices E, F and G, as a matrix will be positive or negative semidefinite when its eigenvalues are positive or negative respectively. Therefore, we included these curvature checks in Annex 16 to verify if matrix E is indeed negative semi-definite and matrix F and G are positive semi-definite. Hence, we can confirm that these conditions are met for all regions. Also, we note that all marginal costs (with respect to output quantities) are found to be positive as well, which indicates the (only) *ex-ante* imposed monotonicity condition is fulfilled.

In the Stata program, we also include several methods to verify the goodness of fit of the estimates obtained by our model. A simple way to apprehend how well the estimations approximate reality, is to perform a linear regression of the observed variables on their estimates and consequently analyse the obtained regression coefficients. A good model will obviously result in a slope-value close to one, a constant close to zero (i.e., a 45-degree line through the origin) and a high R^2. These linear regressions were performed for the input demands and total cost. Annex 17 contains a table with the results of these regression of the observed on the predicted values (including a farm's fixed effect). We ascertain that the goodness of fit is in general more than acceptable, as most slope coefficients are very close to one, and the R^2 values are genuinely high. However, we do sometimes observe a considerable and significantly positive constant, indicating that we tend to underestimate the input demands for low values (except for the non-land capital input, for which it is the opposite case). Note that the regression of animal-specific input demands deviates the most from the 45-degree line. However, as this analysis only concerns crop farms, this is not of major concern. The predicted demands for the other input categories, as well as the predicted total costs, do approximate the observed values rather nicely. All in all, we conclude that our model adequately approximates the data and that the required conditions for a well-behaved and theoretically consistent cost function are sufficiently met to allow us to continue our analysis.

5.3. Estimation results and discussion

After having validated our model and its estimators, we can turn our attention to the analysis and interpretation of the different economic and productivity-related indicators, as introduced in Paragraph 3.4.1. Table 7 therefore provides an overview of these results for the different regions. The year-by-year estimations of these indicators and further details are presented by the different tables in Annex 18. Unfortunately, for some indicators we establish many missing observations for some years in West France and Central Spain. These observations are missing because they are identified as an outlier (*ex-post*), based on the Chauvenet's criterion, and therefore not taken into account for the reported statistics. Remarkably, we observe considerable differences between the three regions. Concerning the estimates related to economies of scale and scope (i.e., ORTS, PSRTS and ESCP), we performed *t*-tests in search for a significant indication of their presence (i.e., a mean value greater than 1). As it turns out, we do find some evidence for this, in particular in France. The ORTS in Central France is significantly greater than 1, indicating that it could be favourable for (some) farms to increase production. However, when we look at the PSRTS, this result is mainly applicable to the region's industrial crop sector. As we are mainly interested in cereal production, these results indicating the presence of economies of scale in Central France is of minor importance to us. Moreover, while the mean of the ORTS is greater than 1, the median suggests otherwise, which indicates some extreme values (probably found in the industrial crop sector) have a considerable impact on the mean. Note the fact that this is the only region for which we obtain a significant indication of the presence of economies of scope. Hence it might be profitable for crop farms to diversify their production, especially towards potatoes, sugar beets and other industrial crops.

Table 7. Summary of estimated indicators (weighted results).

	Central France (FR2)					West France (FR5)					Central Spain (ES4)				
Variable	Mean	SD	Min.	Max.	Median	Mean	SD	Min.	Max.	Median	Mean	SD	Min.	Max.	Median
ORTS	1.0867*	0. 1309	0.8785	1.6458	0.9985	1.0708*	0.0454	0.9050	1.2146	1.0683	0.9954	0.0107	0.9314	1.0375	0.9997
PSRTS															
Animal output	0.9999	0.0001	0.9993	1.0004	0.9999	1.0359*(!)	0.0078	1.0143	1.0586	1.0366	1.0191*	0.0110	1.0030	1.0488	1.0168
Dry pulses and oilseeds	0.9865	0.0022	0.9770	0.9906	0.9868	0.9894	0.0082	0.9566	0.9999	0.9914	0.9947	0.0035	0.9811	0.9993	0.9952
Industrial crops	1.7417*	0.1054	1.5467	2.0809	1.7309	1.0123*(!)	0.0208	0.9430	1.0437	1.0145	0.9814	0.0156	0.9175	0.9998	0.9862
Cereals	0.9998	0.0002	0.9991	1.0001	0.9999	1.1288*	0.0554	0.9793	1.3130	1.1145	1.0000	0.0000	1.0000	1.0000	1.0000
Other crops	0.9938	0.0049	0.9748	1.0005	0.9952	0.9599	0.0340	0.8563	1.0007	0.9687	0.9055(!)	0.0559	0.6949	0.9646	0.9290
ESCP	1.0006*	0.0005	0.9987	1.0030	1.0004	0.9951	0.0056	0.9692	1.0191	0.9961	1.0000	6.1e-07	1.0000	1.0000	1.0000
RMCD (1)															
Animal output	1.5261	0.7685	0.3986	4.0596	1.3075	-2.2203(!)	8.7664	-19.686	11.472	-0.8995	3.6722	17.816	-37.350	30.415	12.023
Dry pulses and oilseeds	0.8782	0.2883	0.3982	1.7399	0.8441	-3.6022	1.0939	-5.1745	-1.0361	-3.9034	5.1538	12.668	-21.209	24.607	11.837
Industrial crops	1.4405	0.5509	0.5771	3.1666	1.2861	-7.4136(!)	5.2824	-13.681	4.8201	-10.305	4.0604	0.7712	1.1728	5.1381	4.2868
Cereals	4.2164	1.3273	2.2876	7.7924	3.9873	5.3924	1.0260	1.8706	8.7930	5.3777	4.5703	1.0883	1.0129	6.1191	4.8376
Other crops	1.2290(!)	0.3978	0.6059	2.2556	1.1865	-0.9840	2.6550	-6.2565	3.7400	-1.4603	9.9896(!)	8.0538	-17.100	17.959	12.374
RCD (1)	2.6087	0.9584	0.5457	6.1362	2.4693	2.4974	2.0320	-5.1260	6.1453	2.9612	4.9070	2.9965	-7.6858	17.337	4.9089
RTC (2)	0.6206	0.2038	0.0844	1.3022	0.6070	0.9575	0.8519	-1.4443	3.4609	0.9851	1.3720	0.8196	-1.7301	2.5289	1.5233
FBTC (2)															
Animal-specific inputs	-1.7011	0.9425	-5.1799	-0.3397	-1.4326	-2.3362	0.7956	-5.2874	-0.9793	-2.1117	-4.7947	1.5892	-12.131	-1.4563	-4.3941
Crop-specific inputs	-0.4201	0.5474	-2.3080	1.4745	-0.4453	-0.6423	2.1994	-5.0833	6.7186	-0.9804	-2.3181	2.0705	-8.9553	6.0269	-2.7630
Other inputs	-1.2340	0.9078	-4.8146	1.6968	-1.1807	-0.0159	2.7541	-8.0285	7.9399	-0.1028	-3.2930	3.7309	-19.413	14.043	-3.7534
Non-land capital	-7.3416	4.1146	-22.934	-2.4104	-6.0755	-10.537(!)	7.6724	-60.448	1.6314	-7.8355	-41.061(!)	37.244	-256.08	-8.2414	-27.645

(1) *in nominal % per year*
(2) *% per year*

* significantly greater than 1
(!) one or more years with zero or very few observations

[ORTS: overall returns to scale; PSRTS: product-specific returns to scale; ESCP: economies of scope; RMCD: rates of marginal cost diminution; RCD: rate of (total) cost diminution; RTC: rate of technical change; FBTC: factor biased technical change]

For West France on the other hand, we do find significant evidence of the presence of economies of scale for the cereal (and industrial crop) producing farms, implying that total incremental costs will rise less than proportionately as their production increases. Hence, it is important to further investigate the reasons impeding these farms from expanding and attain a long-run equilibrium in which marginal costs equal average costs (e.g., liquidity constraints, limited availability of agricultural lands or labour, etc.). As becomes apparent from the descriptive statistics derived from the EU-FADN data (Table 5) and the data from Eurostat (Table 4), the farms in West-France tend to be smaller than those of Central France. It's possible that the transition towards bigger farms in West France is lagging behind in comparison to the farm expansion process in Central France. Note however, that these statistic descriptive statistics suggest as well that farms in Central Spain are considerably smaller compared to the other two regions. Nonetheless, we do not find any significant evidence of the presence of economies of scale in Central Spain (with the less important exception of the PSRT of animal output). Hence, it seems that the fact of having many small (but efficient) farms is not by definition disadvantageous, but depends upon the region. A final remark we wish to make concerning these indicators is that these indications are only based on averages. Therefore, the possibility of their presence can off course not be excluded for particular groups of crop farms, even though the region-wide average level suggests otherwise. However, taking these considerable regional differences into account, one should be very careful when claiming the general presence of economies of scale and/or scope, without bringing accurate evidence and without specifying exactly to which (sub)sector this claim would be related to. It would be an interesting extension of this work to examine if economies of scale and/or scope might occur for particular farm categories (e.g., maybe it does occur for organic crop farms, or only for farms with high capital inputs, etc.).

We now divert our attention to the other productivity-related indicators. The estimated rates of marginal cost diminution differ strongly for the different output categories and the different regions. Again, we are mainly interested here in the rates for the cereal output category. Across the three regions, the rate of marginal cost diminution for this category was positive and, on average, of the same order of magnitude. With an average annual marginal cost diminution of 5.4% for cereal production, West France achieved the highest rate of the three regions. Remarkably however, at the same time this region achieved the worst (negative!) average rates for all other output categories. These negative rates indicate that marginal costs have been increasing on average over this period. This alarming trend is only observed for this region. In Central France and Central Spain, marginal costs have been decreasing in general for each output category, although there have been a lot of fluctuations according to the high standard deviations. One thing we have to note, is that for some output categories, only few or even zero observations are taken into account, which might lead to biased outcomes. All in all, the most important conclusions that can be drawn concerning the estimates of the RMCD, is that the results suggest Central Spain was generally the best performing region on average over this period, and that the marginal costs for cereal production have decreased for each region. However, the RMCD for cereal production tends to decrease near the end of the sample period for the regions of West France and Central Spain (Annex 19).

Concerning the rate of total cost diminution, we see that Central Spain achieved the highest average rate of the three regions, albeit with a relatively high standard deviation. This average is approximately double as high as the two French regions, which have a comparable average level of RCD. However, the standard deviation for West-France is considerably high, a fact that also becomes apparent when analysing the evolutionary patter of these estimates. Therefore, we plot the rates of total cost diminution, along with the rates of marginal cost diminution for the cereal production and the rate of technical change, over time (Annex 19). In contrast to what the simple overall average values might indicate, it becomes apparent that the evolutionary patterns of these indicators strongly differ between the three regions. For instance, when we look at the region of Central Spain, we see that the rate of cost diminution was very high in the early and mid-1990s, and has been declining ever since. This region even reaches slightly negative rates at the end of our sample period (indicating an increase in total cost!). In contrast, the rate of cost diminution in Central France has been gradually increasing until 2006, before falling back to a relatively constant and healthy level of approximately three percent. What is more alarming though, is the trajectory revealed for West France. Since 1992, both the rate of cost diminution and technical change have been declining and have reached considerable negative values during the last years of the investigated period. Unfortunately, we have not yet been able to implement additional data. It would be very interesting to see whether these negative trends continue for both West France and Central Spain, or whether they were due to unusual circumstances during the last year(s) of our sample period.

For the rate of technical change, we observe similar patterns as those for the rate of cost diminution. In particular for Central France, this rate has maintained a relative stable level throughout the period 1989 – 2011. Unfortunately, it has been declining for the other two regions along with the rates of cost diminution. Note that, although having the lowest average level of RTC, Central France exhibits the most favourable evolutionary pattern, thanks to the steady rate at which the technical change has been evolving. Therefore, one should be careful in making conclusions concerning regional performances if only the average rates are taken into account, as it turns out they might be very misleading. Again, additional data would have been of great value in order to determine whether these alarming trends have persevered or not. If we now reconsider the pending question of our literature review, i.e. whether there has been a slowdown in agricultural productivity gains or not, we have to conclude that the answers are very region-specific. In the case of Central France, we certainly do not find any convincing evidence to confirm a slowdown, whereas we do find strong indications that this might be the case for the other two regions. It is therefore crucial to continue carefully monitoring the further developments of these indicators to assess if one should intervene or not (e.g., redirect R&D towards technologies particularly suited for those problematic regions). In conclusion, an important lesson learned from the estimations of the rates of (marginal) cost diminution and technical change is the possible occurrence of a large heterogeneity in their evolutionary patterns and present values, even within the same country (e.g., France). Note that this (crucial) information might have been left unobserved in more macroeconomic oriented studies at the sectoral or country level and studies only reporting average estimates of performance indicators.

The final indicators in Table 9 report the factor biased technical change. Unfortunately, we encounter an issue for the estimates of input category 'non-land capital' in West France and Central Spain due to missing values for several years, because they have been identified as outliers *ex-post*. Therefore, it seems we obtain some unrealistically high estimates for the FBTC estimates (in absolute value). A limitation in time meant we could not further elaborate a solution to this problem (e.g., implementing an alternative way of identifying outliers). On the other hand, no problems were encountered for the region of Central France. So, looking at these estimates, we conclude that the technical change was saving in all input categories. Remarkably, we observe high (absolute) values for factor biased technical change in the non-land capital input category, which is not very intuitive, as we would expect that nowadays new technologies are more capital intensive. Due to the encountered problems in the other regions, we cannot confirm whether this is also the case in the other regions. Looking at the other input categories, we see that the FBTC for animal-specific inputs were also relatively high (again in absolute value), however, this measure is not of great importance for the scope of this analysis. Fortunately, the technical change for crop farms was also saving in crop-specific inputs. This might indicate a relatively reduced use of mineral fertilizers and chemical pesticides, which could imply a transition towards more sustainable agricultural practices or an increase in organic farming for example. Although the framework (as applied here) does not permit to thoroughly test for these kinds of statements.

5.4. Possible determinants underlying productivity gains

As discussed in Paragraph 3.4.2, the final step of the Stata procedure is the determination of the factors underlying the estimated rates of cost diminution, technical change and marginal cost diminution of cereal production (which we will not specify each time again hereafter). Therefore, we perform regressions of these rates on different indicators in order to retrieve the corresponding correlation coefficients. For these regressions, rather than performing a linear regression, we use a ln-transformation for the different dependent and independent variables (except for the TC-residuals and dummy variables for the years and subregions). By performing the ln-transformation, we obtain directly the elasticities for the different variables. Once again, we had to decide on the type of standard error reported by the regressions: either we cluster them by year or we request robust standard errors. Therefore, we proceed in the same way as discussed in section 5.1.1 for the specification of the type of standard errors in the NLSUR command for the estimation of the system of input demand equations. This time however, a clear pattern could be observed when plotting (the means of) the squared residuals over time (cf. Annex 20.1). Due to this consistent (exponential) increase of the squared residuals, we decided to cluster the observations by year. In doing so, we allow for intragroup correlation. That is to say, the observations are independent across groups, but not necessarily within groups. Note as well that, according to the RVF-plots (i.e., the postestimation diagnostic plots of the residuals against the fitted values) generated by Stata, the presence of a severe heteroscedasticity issue seems very limited (cf. Annex 20.2).

Due to space limitations, we are not able to report all correlation coefficients in a clear way in this section. Therefore, we provide a neat summary of the correlations established by the different regressions in Table 8 and refer the reader to Annex 21 for further details concerning these estimations. Table 8 indicates whether a positive (*+*), negative (-) or non-significant (*NS*) correlation has been established between the RCD, RTC and RMCD, and the explanatory variables. This table, however, excludes the correlations obtained for the different dummy variables, indicating the different subregions and years, and which were included in the same regressions. An overview of the number of significant dummy variables for the subregions are provided in Table 9. Concerning the significance of the dummy variables for the different years, Stata is unable to retrieve the correlation-coefficients for the year 2011, due to collinearity problems. Apart from this issue, all time-dummy variables turn out to be highly significant. These coefficients were also plotted over time for each region, as depicted in

Annex 20.3. Note as well that these time-coefficients attributed to the generally high R^2 values. Besides the estimation of the correlation coefficients, the framework allows to generate several other postestimation diagnostic plots related to these regressions. Besides the previously mentioned RVF plots (i.e., the plots of the residuals against the fitted values), these include the RVP-plots (i.e., the residual-versus-predictor plots) and the AV-plots (i.e., the added-variable plots) as well. From the RVP-plots, we can deduct due to which variable(s) a heteroscedasticity problem could arise. However, no particular variable was found to clearly induce a heteroscedasticity problem, apart from the degree of farm specialization in Central Spain to some extent. The other category of postestimation diagnostic plots are the AV-plots for different explanatory variables. These plots attempt to show the effect of adding another variable to a model already having one or more independent variables. In other words, rather than taking only one explanatory variable and the dependent variable into account, an AV-plot also take the effect of other independent variables in the model into account (i.e., it holds all other explanatory variables constant). Hence, these AV-plots give a good indication of the nature of the relationship between the considered explanatory variable and the dependent variable, and the way the different observations are scattered around the fitted line (with a slope equal to the correlation-coefficient). As expected, the observations are scattered nicely around the fitted line in the case of those explanatory variables for which a (highly) significant correlation-coefficient was established. Note that because we hence obtain 90 additional plots in total (i.e., all RVP-plots and AV-plots combined), not all of them are reported here, as this would be too extensive for this work. We therefore only included the AV-plots of the significant determinants for the different productivity indicators in Annex 22.

Another postestimation tool provided by Stata is the OV-test, or 'omitted variable' test. Thereby, Stata will perform two versions of the Ramsey (1969) regression specification-error test for omitted variables. This test amounts to fitting $y = xb + zt + u$ and then testing $t = 0$, while powers of the fitted values are used for z. In doing so, we test whether non-linear combinations of the explanatory variables have any power in explaining the dependent variable. If t tends to differ strongly from 0, then this might be an indication that the dependent variable might be better approximated by another non-linear functional form. The results of these test suggest indeed for each regression to reject the null-hypothesis (i.e., the model has no omitted variables), implying that another functional form might be more suited. However, we performed several regressions without the ln-transformation and using linear and quadratic functional forms. Unfortunately, neither were able to improve the outcome of the OV-test. Hence, we decided to keep the ln-transformation, because it has the advantage of providing directly the elasticities. However, we note that there might still be room left for improvement related to this issue. During the following paragraphs, we will discuss one-by-one the correlations established for the different explanatory variables. We will discuss how clear the overall correlation (across regions) is, suggest some possible interpretations and explanations for our different findings and we will relate them with our initial hypotheses.

Table 8. Overview of the established correlations of the linear regressions of RCD, RTC and RMCD on the different indicators for the different regions, and their expected signs according to the *ex-ante* constructed hypotheses.

Variable	**Expected sign**	**Rate of cost diminution**			**Rate of technical change**			**Rate of marginal cost diminution**		
		Central France $R^2 = 0.882$	West France $R^2 = 0.403$	Central Spain $R^2 = 0.578$	Central France $R^2 = 0.889$	West France $R^2 = 0.622$	Central Spain $R^2 = 0.347$	Central France $R^2 = 0.984$	West France $R^2 = 0.922$	Central Spain $R^2 = 0.988$
Size	+	-	NS	NS	-	NS	-	-	-	+
Degree of farm specialization	+	+	+	NS	+	+	+	-	-	NS
Capital per AWU	+	+	-	NS	+	-	NS	+	-	-
Capital per size	+	-	+	NS	-	+	NS	-	+	+
Land ownership	+	+	NS	+	+	NS	+	+	NS	NS
Subsidy ratio	-	NS	NS	+	NS	NS	-	-	NS	+
Intensity of crop prod.	+	-	NS	NS	+	+	+	-	-	NS
Yields of wheat	+	-	-	+	-	-	-	-	+	NS
Törnqvist price index	-	+	-	+	+	-	+	+	-	+
TC residual	+	NS	NS	-	NS	NS	-	NS	NS	-

+ : positive correlation
- : negative correlation
NS : non-significant correlation

Table 9. Number of statistically significant correlation-coefficients for the dummy variables for the subregions

	Rate of cost diminution			**Rate of technical change**			**Rate of marginal cost diminution**		
	Central France	West France	Central Spain	Central France	West France	Central Spain	Central France	West France	Central Spain
Subregions	5/5	2/2	2/2	4/5	1/2	1/2	4/5	2/2	2/2

First, it has to be noted that some attributions turn out to be very region-specific, and that one needs to be very careful in making strong conclusions based on only three regions. Also, because we opted for a ln-transformation for both the dependent and most of the independent variables, the coefficients represent the elasticities between the variables. For instance, the regression for Central France indicates a significant correlation coefficient of -0.101 between the dependent variable $\ln(RCD)$, and independent variable $\ln(size)$, which can be interpreted as follows: a ten percent increase in the TUAA of a farm (representing its size), will decrease the rate of marginal cost diminution by approximately 1.01 percent according to this regression in this region, ceteris paribus. The interested reader can extend this interpretation for the other correlation-coefficients retrieved by each regression.

The first explanatory variable possibly attributing to the productivity indicators, is the *farm's size* (expressed in hectares of TUAA). This variable was included to verify the first hypothesis, which suggests that larger farms will achieve higher productivity gains, because they might benefit from technological economies of scale and lower input prices. However, according to our results, we rather obtain a negative correlation. This is similar to what was previously established, namely that we do not find any general and significant indication for economies of scale. This means that large farms do not achieve by definition higher productivity gains, which is at odds with a more common view. In contrast, our results indicate that smaller (but highly efficient) farms are able to adopt new technologies sooner and to achieve high productivity gains as well. For instance, they might be more flexible in trying out new technologies, attributing to higher productivity gains. Also, in comparison with large farms, small farms are often able to monitor their production more carefully and detect possible threats to their production activities at an earlier stage (e.g., plant diseases, sick animals, etc.), which is often a challenge for large farms with very occupied managers, a huge herd, enormous fields and many hired (seasonal) employers.

The second hypothesis that can be assessed is the claim that more *specialized farms* have higher rates of cost diminution and technical change. Our results indicate that this can be validated, as a predominant positive correlation can be established, in particular for the RCD and RTC. This is also confirmed by the study conducted by Wieck & Heckelei (2007). The positive correlation coefficients suggest indeed that specialized farms have good access to (new) technology and show on average better performance in managing the production process. A higher degree of specialization enables one to focus specifically on achieving the highest productivity level possible for a particular output, instead of having to split his attention and knowledge over a number of outputs and their correlated technologies. It also makes very crop-specific investments more profitable, thereby increasing the probability of the adoption of new (expensive) specialised technologies and specific equipment, which are both beneficial for productivity growth. To illustrate, when the share of cereal output in total farm output (i.e., the degree of farm specialization) increases by 1 percent, the RTC will increase by 0.487 percent, 1.058 percent and 0.191 percent in Central France, West France and Central Spain respectively, ceteris paribus. Therefore, one might be tempted to encourage farm specialization to the extreme, for instance by adopting certain favouring policies. However, this imposes a high risk for the producers in years of bad harvests, due to adverse weather conditions or disease outbreaks and epidemics for example. For farmers, this is often the main reason impeding them from further specialization. Therefore, this kind of policies should be combined with certain guarantees of compensations in case of bad harvests, in order to successfully favour farm specialization and its associated productivity gains. Note that the correlation with RMCD tends to be rather negative. As a farm becomes more specialized by producing relatively more of a particular output, marginal costs tend to increase according to theory, explaining the negative correlations with the RMCD.

Next, we turn our attention to the correlations obtained for the *capital per labour unit and per farm size* (in hectare). Here we have to conclude that no strong indications were obtained to validate or reject our hypotheses. These hypotheses suggest that more capital will increase the rates of cost diminution and technical change. For Central France, the hypothesis for capital per AWU seems to hold, in contrast to West France. For the latter, we do however obtain a strong indication that the positive correlation between the capital per size and the RTC seems to hold. Hence, relative small farms with relatively more capital might achieve higher productivity gains, as they seem to adopt new technologies etc. more easily. This seems to be in line with our previous conclusions related to the correlation with a farm's size and the productivity indicators: smaller farms are not per se disadvantaged when it comes to achieving productivity gains.

The consequent explanatory variable, i.e., the *land ownership ratio*, yields interesting and coherent correlations as well. The objective of this correlation was to determine whether the effects of (land) tenure security could be detected. And indeed, the obtained correlations are all positive (or non-significant), indicating that owning a higher share of utilized lands is beneficial for productivity. Land in ownership guarantees the payoff of long-term investments attributing to productivity. If we assume that a higher ownership ratio leads to more investments and sustainable agricultural practices, this will not only be rewarding for the farmers themselves, but might also be beneficial for the regions' environmental conditions. In general, sustainable agriculture will lead to more biodiversity, better soil conditions, less soil erosion, less air and water pollution, more efficient use of resources, healthier food for the consumer, and many more (Asami, Hong, Barrett & Mitchell, 2003; Lichtfouse, Navarrete, Debaeke, Souchère & Alberola, 2009). Therefore, policy makers should be very concerned about the tenure security problem farmers face (even within developed agricultural systems), as the positive correlation with productivity gains is clearly established in this analysis. Especially nowadays, as (agricultural) lands become more and more scarce and valuable. This might open the gates for opportunistic outsiders investing in agricultural lands, trying to extract rents out of them, which would be detrimental for the agricultural sector. Therefore, legislation concerning agricultural tenancy, agreements for the lease of lands, and regulations on sales and auctions of farmland should be assessed and kept up to date on a regularly basis, in order to protect farmers and to ensure sufficient land tenure security for them.

Concerning the *subsidy ratio* (i.e., the share of a farm's cost covered by subsidies), we don't find strong indications for them to have a negative correlation with the rate of cost diminution and technical change. Remember that the meta-analysis of Minviel & Latruffe (2017) also suggests it is hard to find conclusive evidence concerning this matter, as many previous studies have already found positive, as well as negative and non-significant influences. Hence, we cannot confirm our hypothesis that receiving high subsidies reduces the incentives to reduce costs to an absolute minimum either. Again, this topic is of high interest for EU policy makers, notably when evaluating and reforming the CAP, because subsidising the agricultural sector is heavily debated within the EU. As introduced in the beginning of this work, productivity gains are crucial to maintain a sector at a competitive level. Thus, if this hypothesis had been validated, distributing subsidies to support farmers might actually be harmful for the sector's competitiveness itself, even though they might be indispensable for (some) farmers to survive. However, as we do not find any strong indication to either validate or reject the hypothesis, further investigation should be conducted. For instance, using other functional forms for the regression, or examine whether specific types of subsidies do have a significant impact. One of these types might be subsidies that are distributed specifically to encourage the adoption of new technologies. This type might be more effective for achieving productivity gains than (decoupled) direct payments in general. Hence, it would be interesting to see whether other correlations could be established in doing so. Finally note that Latruffe et al. (2017) obtained heterogeneous findings as well during their examination of the association between agricultural subsidies and dairy farm technical efficiency. They also state it would be useful to disentangle the possible differential effects of various subsidies on technical efficiency, as they find that some of the countries that kept the highest possible degree of direct payments linked to crops and livestock when decoupled payments were introduced, exhibit a positive relationship between subsidies and technical efficiency.

Moving on to the next explanatory variable, which is the *degree of (chemical) intensification* of the crop production, we find a positive correlation with the rate of technical change. Hence, we conclude that a more intensive use of seeds, fertilizers, pesticides and/or other highly efficient crop-specific inputs might attribute to productivity gains, thereby confirming our hypothesis. Note that the productivity gains thus obtained, might only occur in the short-term and have a negative long-term effect. However, we do find rather negative correlations for the rate of total and marginal cost diminution. One possible explanation for this is that, although this intensification leads to higher productivity levels/RTC (i.e., producing more output with relatively fewer inputs), these are expensive products and technologies, and as a result, these productivity gains or technical changes might not be translated into high cost reductions.

Then, taking the *wheat yields* into account, we observe mainly negative correlations, especially for the rate of technical change. In theory, the expected sign of the correlation depends on whether we consider yields as an exogenous or endogenous variable. If yields are taken as an exogenous variable representing favourable agro-climatic conditions or high farm efficiency, then we may expect a positive correlation, as higher yields bring lower marginal costs, as is found by Wieck & Heckelei (2007). However, if yields are taken as an endogenous variable, that can vary depending on the degree of intensification, we may expect a negative correlation, since then higher yields bring higher marginal costs, as predicted by theory (i.e., producing one additional unit becomes more and more expensive). Also, as suggested in the introduction of the hypothesis, high yields might reduce the incentives to reduce costs to an absolute minimum or to adopt new technologies, etc. Hence, based on our analysis, we conclude (at least one of) the last two explanations predominate(s), as we mainly observe negative correlations between the yields and the productivity indicators.

Consequently, we take the *price* indices into account. According to the hypothesis, we should observe mainly negative correlations, as low prices force farms to better control their costs and low price (expectations) will reduce production and therefore marginal costs, for instance. However, this only seems to hold for the region of West France, as we obtain positive correlation coefficients elsewhere. These positive correlations indicate that high prices contribute to high productivity gains (or vice versa), which is in contradiction with the findings of Wieck & Heckelei (2007). However, in their study, Wieck & Heckelei (2007) only focussed on dairy production. In comparison, crop farms have often more possibilities to diversify in case of low output prices (e.g., switching to producing other types of better-priced cereals or switch to industrial crops, etc.), whereas dairy farms have less choice. Their 'only' possibility is often to reduce production and hence (marginal) costs. Therefore, because crop farmers in our case might switch to producing more of the other (higher priced) cereals, this might mitigate the counter-intuitive outcome. Another possible explanation for this counter-intuitive outcome, especially related to the RCD and RTC, is that high prices will attract the attention of producers, leading to maximal efforts and additional investments to make these activities as profitable as possible, leading to high RCD and RTC.

Another very clear outcome is the non-significance of the *total cost residuals* in the different regressions (with the exception of Central Spain). Note that these were presumed to approximate the degree of a farm's inefficiency. Hence, a farm with a high degree of inefficiency is supposed to have a great margin for improvement left, which could be easily achieved by just copying the technologies and agricultural practices of the regions' better performing farms. However, when inserting these residuals into the regressions as explanatory variables, the vast majority turns out to have non-significant correlation-coefficients. Two straightforward explanations can be given. Either this catch-up effect does not happen and the inefficient farms continue to lag behind the others. For instance, either the technology used by better performing farms, is not that easy to observe and/or to copy, or either these farms face certain liquidity constraints, preventing them from investing in the technologies that would raise their productivity. Another possible explanation for the clear non-significance of these correlation-coefficients is that the total cost residuals simply do not effectively represent a farms' inefficiency. As mentioned previously, many other unobserved factors might enter in these residuals as well. Hence, a problem arises when these unobserved (or non-measurable) factors affect the costs a farm faces, but are not related to its inefficiency. For instance, we already mentioned the effect of having many stones in one's field, but we can also give the example of low-located fields highly susceptible to inundations. These factors obviously raise a farm's costs, as these they need to invest in heavier equipment, such as very robust plows and cultivators, or draining systems. And because they are not represented in the cost function, they will be captured by an increase in the residuals. However, they do not represent a higher degree of inefficiency. Thus, both reasonings might explain why we obtain these non-significant correlation-coefficients.

Let us divert our attention now to the significance obtained for the dummy variables for the different *subregions*. According to the hypothesis, the rates of cost diminution and technological change should differ between subregions. Taking into account the high number of significant dummy variables, we can validate this hypothesis according to this framework: there is a significant difference in the productivity gains achieved by different subregions. For most productivity related-indicators, most subregions differ significantly from the reference subregion. There are several possible explanations to substantiate these inter-subregional differences. For instance, climate conditions can differ slightly between subregions, as some are located near the coast (e.g., Lower Normandy) and others rather inland (e.g., Burgundy). Another explanation could be the existence of better regional cooperatives, research institutes, and agricultural associations or unions for farmers where they can share their knowledge and knowhow amongst each other. We can think as well of varying soil compositions, different local policies, possible welfare differences, heterogenous environmental evolutions, etc., attributing to these inter-subregional differences.

Finally, we already noted the series of highly significant dummy variables for the different *years*, which are plotted in Annex 20.3. Unsurprisingly, they show similar patterns as the plots previously discussed concerning the patterns of RCD, RTC and RMCD over time, except that here we also control for the other determinants underlying these rates (e.g., output prices, yields, etc.). Note that these estimated time coefficients are relatively high in the case of Central Spain in comparison with the other two regions, because many other determinants were found to be non-significant here. Hence, those time-coefficients are relied upon to account for a relatively larger share in the explanation of the estimated productivity gains. According to the hypothesis, these time-coefficients should be positive and increasing over time. Concerning Central-France, this seems to hold at least until the year 2006, after which these time coefficients tend to drop. It is however unclear whether this represents a persevering slowdown in productivity growth or just unusual circumstances, as we do not have enough years available after 2006. When looking at the plots for Central Spain, we observe similar behaviour, which might indicate that these drops in productivity gains might indeed have been caused by unusual circumstances, such as general bad weather conditions, disease outbreaks or fluctuations in input prices (the latter impacting the RCD in particular). However, here we observe an alarming trend in West France once again, as most time-coefficients turn out to be significantly negative (when opposed to the reference year 1989). These might indicate the negative effects of unsustainable agricultural practices (i.e., those that have not yet been accounted for by any other independent variable), or even the emerging effects of climate change. Hence, while the validation of this hypothesis can be disputed for Central France and Central Spain, it can certainly be rejected for West France, according to these outcomes.

To end this section, we conclude that we were able to confirm the majority of the hypothesis we constructed *ex-ante*, although, at the same time, we obtained some unexpected correlations for some variables as well. However, our approach of just estimating correlation coefficients using a ln-transformed regression, is a relatively simple and easy way for merely establishing the existence and direction of any relationship between the productivity indicators and the different explanatory variables. Note that the estimated elasticities in these regressions only hold in a ‘ceteris paribus’ context and might suffer from an omitted variable bias. Also, an endogeneity problem might occur for the different explanatory variables included in the regression. For a more profound analysis, such as precisely quantifying these different effects or when aiming to use it as a predictive tool for these indicators, one will need to develop a more complex approach. For instance, further investigation of a non-linear functional form (as suggested by the OV-test) might yield interesting improvements.

6. Conclusions

6.1. General discussion

Building further upon previous studies, we have developed throughout this work a performant framework that can be particularly useful for productivity analysis. The key of the approach is the estimation of a well-behaved and theoretically consistent cost function, using a flexible SGM functional form. Afterwards, these estimates are used to compute a series of economic and productivity-related indicators. One of the main advantages is its capability of handling microeconomic data. The associated Stata estimation procedure is therefore specifically designed for processing EU-FADN data. Moreover, these Stata routines are generally very user-friendly and easily customisable, in order to obtain the estimations with all desired properties for any region or Member State. These properties include the monotonicity restrictions, the curvature restrictions, the farm type and other farm characteristics, the aggregation scheme, the time period, the time horizon, the number of outlier removal loops, etc. The Stata routine consists of four main stages. During the first stage (i.e., data preparation), the EU-FADN databases are imported for the different years, missing prices are retrieved from external databases (mainly from Eurostat) and price indices are constructed. The second stage's (i.e., data aggregation) purpose is to aggregate this data according to a particular aggregation scheme for a specific region and farm type. Afterwards, in the third stage, the system of input demands is estimated according to a non-linear seemingly unrelated regression. Using these estimates, the total cost function is constructed. After having validated these estimates, the different indicators related to the actual productivity analysis can be generated. These indicators are further investigated in the fourth stage, during which we establish correlation-coefficients in search for the determinants underlying these productivity indicators.

To demonstrate the capabilities of our framework, we performed this routine for the crop farms located in the three most important regions for cereal production in the EU, i.e., Central France, West France and Central Spain. During the estimation process, an acceptable number of outliers was removed before obtaining the final regression coefficients, of which the majority differed significantly from zero. After having validated these estimates, we found considerable differences in the performances of the three regions. First of all, the results suggest that economies of scale are of relative minor importance in Central France and Central Spain, but they might be present in West France. Evidence of economies of scope on the other hand, was only found in Central France.

Concerning the productivity-related indicators, we found an average annual rate of cost diminution of 2.61%, 2.50% and 4.91% for Central France, West France and Central Spain respectively. The annual average rate of technological change was estimated respectively at 0.62%, 0.96% and 1.37% for the same regions. However, it was only when we plotted these annual average rates over time for the different regions, that the vast heterogeneity of their evolutionary patterns became apparent. Even the difference between these patterns of two neighbouring regions within the same country, i.e., Central and West France, was astonishing: whereas both the RCD and RTC have been increasing up until 2006, before falling back to a steady (but positive) level in Central France, these rates have been gradually declining over the same period in West France, and even reached negative values for the last three years. Because Central Spain exhibits the same kind of disturbing trend, it is crucial to continue monitoring these indicators in the future, in particular for these two regions, in order to determine whether these negative trends persevere, or whether they are due to abnormal conditions. Unfortunately, while we dispose of two more years of data, we were not yet able to implement them. If it turns out these patterns continue to slope downwards, one should be very concerned, and measures will have to be taken. For instance, more profound analyses should be conducted in search for the causes of these declines. Consequently, R&D could be redirected towards technologies particularly useful for those problematic regions or policies could be adapted in favour of the determinants underlying these productivity gains.

If we now go back to our literature study, we are able to compare our results with the (TFP) measures found by several studies. For comparison, several studies related to the EU for approximately the same period are listed in Table 10, together with the rates of technical change for the three regions investigated in this work.

Table 10. Overview of different studies on productivity gains in the EU.

Study	**Period**	**Country/region**	**Estimated average annual productivity growth**
EC (2014)	2005 – 2013	EU-28	1.0%
		France	0.0%
		Spain	1.7%
Fuglie, Wang & Ball (2012)	1973 – 2002	Western Europe	1.58%
		France	1.36%
		Spain	3.42%
Galanopoulos, Surry & Mattas (2011)	1990 – 2002	Western Europe	1.007%
		France	1.009%
		Spain	1.016%
Leetmaa, Arnade & Kelch (2004)	1973 – 1997	*France*	1.56%
		Spain	1.12%
Rungsuriyawiboon & Lissitsa (2017)	1992 – 2002	Europe	0.807%
		France	2.92%
		Spain	1.58%
Current study	1989 – 2011	*Central France*	0.62%
		West France	0.96%
		Central Spain	1.37%

This table illustrates nicely how estimates of productivity gains can differ from study to study. For instance, in France we find interesting results: the EC (2014) indicates a stagnation in productivity growth over the period 2005 – 2013, while Rungsuriyawiboon & Lissitsa (2017) find an average TFP growth of 2.92% for the period 1992 – 2002. This pattern is somewhat comparable with the RTC evolution we estimated for West France. Also, we established a considerable within-country variation for France, so not only the method and the considered period might explain the variation in estimated productivity growth, but also the data one has at hand, as one region might be better represented compared to others. Concerning the estimates of (Central) Spain, we find more coherent results, as they are all situated within a range of 1.0% and 1.7%, with our estimate of 1.37% almost exactly in the middle of this interval. Note that this is without taking the exceptionally high value of 3.4% into account obtained by Fuglie, Wang & Ball (2012). However, as can be seen in Table 3, this average is strongly biased upwards due to the high productivity gains in the period 1973 – 1982 in Spain, which is not represented in our data. In conclusion, we note that estimates of the average annual productivity growth largely depend upon the method of measurement, the considered time period and the data composition. Moreover, simply comparing averages over certain periods should not be one's main concern. More importantly, one should be interested in their evolutionary patterns and their current tendency to increase or decrease and to converge or diverge, thereby possibly disentangling different regions and/or types of farms. Note as well that, as Alston (2018) demonstrated, significant differences in estimates might also be (partially) explained simply by the fact of using datasets originating from different sources.

Another pending and heavily disputed question addressed during our literature review was whether a slowdown in productivity grow occurs or not. For instance, Fuglie (2010) and others stated there was absolutely no evidence of a slowdown in productivity growth estimates obtained by their studies, which is in direct contradiction with Alston et al. (2015). Our analysis reveals this answer strongly depends upon the considered region. When looking at the annual levels of the RCD, RTC and RMCD for cereal production, we do not have any strong indication of a slowdown in the region of Central France. This region's productivity indicators have been steadily increasing for most of the analysed period. However, a slowdown might have occurred (or is occurring) in West France and Central Spain, as we established a strong and persevering negative pattern of these indicators. Yet, when we consequently account for the different determinants (possibly) attributing to these rates, such as the degree of farm specialization, yields, prices, etc., we do find some positive patterns for the time-coefficients in the regression for Central Spain as well (cf. Annex 20.3) although the explanatory power of these regressions is limited.

Concerning the rest of our analysis on the determinants possibly underlying the estimated productivity gains, we establish that larger farm sizes do not necessarily attribute to higher productivity gains. However, higher degrees of farm specialization and land ownership are positively correlated with productivity gains in all investigated regions, whereas a negative correlation is found for the yields of cereal production. Furthermore, output prices exhibit a positive correlation, with an exception for the region of West France. Finally, we noticed that productivity gains can differ significantly amongst subregions.

6.2. Strengths and limitations

We have shown that we were able to design and empirically implement a performant framework to assess historic productivity gains. Our cost function is capable of handling multiple inputs, multiple outputs and multiple quasi-fixed inputs simultaneously, which is quite exceptional when looking at other studies. Furthermore, the cost function is fully flexible and theoretically consistent. As we emphasized in the introduction, we make use of microeconomic data, allowing us to take full farm heterogeneity into account, rather than performing a sector- or country-wide macroeconomic analysis, which is the case for the vast majority of publications on productivity analysis (cf. Table 10). Hence, using this framework, we are able to not only report the productivity gains achieved by a particular country or region, but also disentangle the productivity gains achieved by particular farm categories within a country or (sub)region. In other words, instead of making a general country-by-country comparison, we are able to compare different types of farms within and across countries, regions or sectors, thereby determining the most important attributions for each type and their tendency to converge or diverge.

The developed approach is generic for the whole EU-FADN data set and, therefore, applicable to any region and member state with enough farm observations for dealing with the requirement in degree of freedom. The benefit of using EU-FADN panel data is that it shows a high degree of balance, i.e., a high degree of repetition of the same farm through the time period. This framework is fully implemented in several relatively straightforward Stata procedures, which can be easily customised in order to perform the estimations for the desired farm type (but also for many other farm characteristics such as location, altitude, size, organic or not, etc., as far as these are reported in the EU-FADN data), time period, time horizon, the functional form, base year, input and output aggregation scheme, region, Member State, theoretical restrictions and estimation through fixed effects or not. The approach is user-friendly since this selection is performed by yes-or-no type of statements in the Stata codes. Routines are devised to take care of missing input and output quantities and prices, negative estimated input demands and marginal costs and estimated coefficients with values that are identical to their initial values and/or show infinite standard error. However, note that the approach requires an intermediate background in microeconomics and econometrics to understand it and interpret its estimation results. It also requires an introduction to EU-FADN (data) and Stata, as it is not a press-to-the-button type of estimation tool for analysing economic behaviour.

The empirical part of this work illustrates the capabilities of the methodology and yields satisfying results. The theoretical restrictions are, in general, fulfilled and the indicators of goodness of fit are more than acceptable. Also, the outlier removal procedure efficaciously rejects an acceptable number of observations. Whereas the outliers were only removed *ex-post* in the previous works applying this framework, they are now removed *ex-ante* with the help of an additional estimation loop. Therefore, a possible estimators' bias induced by these outliers, will be reduced.

The main limitations of our study are the following. Throughout this work, we assume that all farms within the same region share the same technology (i.e., the estimated coefficients are identical for each farm). In certain cases, this might be a strong and not very realistic assumption, as the production technology can differ significantly within regions. For instance, major geographical variations within a region could induce the need for different technologies, for instance, when a (remote) mountainous region close to the coast is separated from the sea by smooth and relatively wide coastal plains. Note that the fixed effect estimation procedure is a way to mitigate this problem, by allowing a certain differentiation between farms. Note as well that the econometric meaning of this assumption does not necessarily relates to the actual fact of producing goods using exactly the same technology, such as the assumption that each crop, dairy or cattle farmer disposes of irrigated fields, automatic milking, free stall barns, etc. Sharing the same technology in the 'econometric sense' assumes that these farmers have access to the same family of technologies or the same range of systems, for instance, a well-developed capital or labour market, which might be violated in less developed regions. However, for the regions we selected for our empiric application, it is not unlikely for this assumption to hold, as markets are well and uniformly developed and differences in other factors (e.g., geography, climate conditions, etc.), are not that extreme across these regions.

Another issue is the fact that we did not thoroughly test the robustness of our results. To test the robustness of the estimated results, we would need to use different economic models (i.e., other functional forms, other approaches of productivity measurement, etc.) and compare the estimated results, which we did not. Apart from testing another model, it would be recommended according to Alston (2018) to compare findings obtained by different datasets derived from different sources, as he showed that considerable differences might occur. However, this would be very complicated in practice, as our Stata routine is specifically designed for handling EU-FADN data.

We also have to note the limitations of the theoretical restrictions, in particular the monotonicity of the cost function in variable input prices and fixed input quantities, which impose highly nonlinear restrictions on parameters during the econometric estimation phase. When the monotonicity restrictions are not imposed *ex-ante*, as it is recommended when imposing *ex-ante* all curvature restrictions, then those monotonicity restrictions are not necessarily respected *ex-post* on some farms, leading to negative input demands for those farms. The fourth limitation of this work is the simplicity of the way we verify the determinants underlying the rates of marginal and total cost diminution and the rate of technical change. The different hypotheses are only validated based on the obtained correlation-coefficients of a ln-transformed regression. This does not reveal any explanation on the mechanisms through which the indicators impact each other and neither does it reveal any information of the causality of the correlation. Moreover, further investigation of the most optimal functional form and implementation of other explanatory variables might yield interesting results. We also addressed the possibility of the occurrence of autocorrelation (i.e., a negative lagged effect of RCD and RTC due to unsustainable practices), which should be further assessed using a better-balanced dataset. Finally, more attention should be attributed to the several years with missing observations when establishing the rates for marginal cost diminution and factor-biased technical change in West France and Central Spain.

An important remark that has to be made as well, is the fact that this work in only intended as an *ex-post* evaluation of productivity gains. It is therefore not capable of providing a projection of future farm expenditures or productivity gains, because, as we noticed during the development of this work, the variations are just too big and too unpredictive to base projections upon. Developing such a tool would therefore be incredibly complicated. Neither is it meant to serve as a tool to simulate the impacts of certain policy reforms for instance.

6.3. Further improvements and extensions

We are far from reaching the boundaries of our framework. We have only provided empirical research concerning crop farms in the three most important regions for cereal production in the EU. However, this could be extended to many other NUTS regions within the EU (if included in the data). Instead of focussing on crop farms, one could also be interested in the productivity gains achieved by cattle or dairy farms of several regions. It would also be interesting to observe the performances of these different types of farms within and across regions to see whether it are the crop, dairy or cattle farms that achieved the highest productivity growth. Note as well that we could also estimate the productivity gains achieved by a particular country as a whole, in order to compare it one-on-one with the results found by other studies in our literature review that adopted a more macroeconomic approach.

Apart from this, extending our dataset with more recent years would also contribute a lot. As mentioned above, it is crucial to continue monitoring the evolutionary pattern of the rates of cost diminution and technical change in order to verify whether certain (negative) trends do or do not persevere. For the moment, data only until 2013 is available, which still leaves an unexplored gap of almost five years between the latest available data and the current situation. Also, the dataset representing the farms in the problematic region of West-France is relatively small. A more extensive database would therefore be useful to see whether other findings are obtained or not.

Next, our framework would be very well suited for studying the convergence behaviour of individual farms. For instance, further analysis of this microeconomic data would enable us to assess whether farms tend to converge to the same productivity level, or if different types of farms or farms with different characteristics (e.g., in farm size, location, etc.) tend to converge to different productivity levels (known as 'club convergence'), or if there doesn't occur any convergence at all. Hence, we could verify several pending hypotheses that would give insight in whether the observed and considerable heterogeneity among farm productivity tends to decrease or not.

To conclude, throughout this work we have demonstrated of being able to obtain many useful and coherent results within the enhanced framework. Just like this work can be regarded as an extension of previous work on itself, there still exist many other or more profound avenues in various directions for future research. Hereby, we really insist once again on the importance of measuring and analysing farm productivity gains, as they are crucial to meet the immense challenges of tomorrow. For that reason, let this work be a source of inspiration for future research, thereby especially encouraging the further exploitation of microeconomic data.

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Farm Productivity Gains in the European Union: a Microeconomic Analysis
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Résumé

Throughout this work, we develop a microeconomic framework for estimating a theoretically consistent, well-behaved, multi-input, multi-output cost function, according to a flexible Symmetric Generalized McFadden (SGM) functional form. Hence, several productivity-related indicators can be computed for their use in a profound productivity analysis. The capabilities of this framework are illustrated by an analysis of the productivity gains achieved by the crop farms located in the three most important regions for cereal production in the European Union, i.e., West and Central France and Central Spain, using microeconomic data obtained by the EU-Farm Accountancy Data Network (EU-FADN) during the period 1989 – 2011. The analysis reveals considerable differences across these regions, mainly regarding their evolutionary patterns. In particular, the regions of West France and Central Spain exhibit an alarming downward sloping trend in their rates of cost diminution and technical change. In a final stage, we attempt to identify several determinants underlying the estimated productivity gains by establishing several correlation-coefficients. We find that a larger farm size does not necessarily attribute to higher productivity gains. Also, higher degrees of farm specialization and land ownership are positively correlated with productivity gains in all investigated regions, whereas a negative correlation is found for the yields of cereal production. Finally, we note that productivity indicators can differ significantly amongst subregions and that a positive correlation can be established between output prices and farm productivity gains, with an exception for the region of West France.

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