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Doctoral Thesis:

“The productive efficiency in agriculture: recent methodological advances”

By

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Abstract

Firm-level productivity and efficiency analyses have important implications for the evaluation of their economic viability and sustainability. The assessment of a firm's performance requires the use of an adequate methodological approach to derive sound efficiency estimates. By targeting economic sectors not previously investigated and using new methodological approaches, this thesis contributes to the literature both from a methodological and empirical point of view.

Three specific objectives have been pursued in three papers that constitute the main body of the present thesis. The main purpose of the first paper is to compare the efficiency ratings of organic and conventional grape farms in Catalonia. To do so, we fit a stochastic production frontier to cross sectional, farm-level data collected from a sample of 141 Catalan farms that specialize in grape growing. Results show that organic farmers, on average, are more efficient than their conventional counterparts (efficiency ratings are on the order of 0.80 and 0.64, respectively). Apart from adoption of organic practices, experience is also found to improve technical efficiency. Conversely, technical efficiency tends to decrease with the relevance of unpaid family labor, farm location in less favored areas, and farmers' concerns for environmental preservation.

In the second paper, local maximum likelihood (LML) methods, recently proposed by Kumbhakar et al. (2007), are applied to assess the technical efficiency of a sample of arable crop Kansas farms. LML techniques overcome the most relevant limitations associated to mainstream parametric and nonparametric frontier models. Results suggest that Kansas farms reach technical efficiency levels on the order of 91%. These results are compared with data envelopment analysis and stochastic frontier analysis efficiency estimates.

The last paper focuses on the assessment of technical and environmental efficiency of Catalan arable crop farms. Specifically, we apply the methodology recently developed by Coelli et al. (2007) and extend it to a consideration of the stochastic conditions under which production takes place, as proposed by Chambers and Quiggin (1998 and 2000). Results suggest that sample farms reach technical and environmental efficiency levels on the order of 93% and 74%, respectively.

Resumen

El análisis de la productividad y la eficiencia tiene importantes implicaciones para la evaluación de la viabilidad económica y la sostenibilidad de las empresas. Dicha evaluación requiere el uso de un enfoque metodológico adecuado que produzca estimaciones de eficiencia no sesgadas. Mediante el estudio de sectores económicos no analizados con anterioridad y la adopción de nuevos enfoques metodológicos, esta tesis contribuye a la literatura, tanto desde el punto de vista metodológico como empírico.

La tesis estudia tres cuestiones principales que se reflejan en tres artículos científicos independientes, que constituyen el elemento central de la misma. El principal objetivo del primer artículo es el de comparar la eficiencia técnica de las explotaciones de uva ecológicas y convencionales en Cataluña. Para ello utilizamos el modelo de la frontera de producción estocástica. El análisis se basa en datos de corte transversal de una muestra de 141 explotaciones catalanas especializadas en la producción de uva. Los resultados sugieren que los agricultores ecológicos son, de promedio, técnicamente más eficientes que los convencionales (los ratios de eficiencia son 0,80 y 0,64, respectivamente). Además de la adopción de técnicas ecológicas, la experiencia también incrementa la eficiencia técnica. En cambio, las explotaciones con una mayor proporción de trabajo no remunerado, que se encuentran en una zona desfavorecida y/o que tienden a tener fuertes preferencias por preservar el medio ambiente, son generalmente menos eficientes.

En el segundo artículo, se utilizan los métodos de máxima verosimilitud local (LML) propuestos recientemente por Kumbhakar et al. (2007) para estimar la eficiencia técnica de una muestra de explotaciones agrícolas especializadas en la producción de cereales, oleaginosas y proteaginosas en Kansas. Las técnicas LML permiten superar muchas de las limitaciones asociadas a los modelos de frontera paramétricos y no paramétricos. Los resultados sugieren que las explotaciones de Kansas son técnicamente eficientes, con niveles de eficiencia del orden del 91%. Estos resultados se comparan con los ratios de eficiencia obtenidos a través del análisis de la envolvente de datos y de la frontera de producción estocástica.

El último artículo se centra en la estimación de la eficiencia técnica y medioambiental de una muestra de explotaciones Catalanas especializadas en la producción de cereales, oleaginosas y proteaginosas. Para ello se aplica una versión ampliada de la metodología desarrollada recientemente por Coelli et al. (2007), la cual se extiende para considerar explícitamente las condiciones estocásticas bajo las cuales tiene lugar la producción. Para ello se utilizan los métodos estado-contingente propuestos por Chambers y Quiggin (1998 y 2000). Los resultados sugieren que las explotaciones presentan niveles de eficiencia técnica y medioambiental del orden del 93% y 74%, respectivamente.

Dedication

I dedicate this doctoral thesis to my mother "Mbarka" and my father "Mohamed "for their patience and sacrifice in making me what I am today.

✍ BOUALI

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Chapter 1

Introduction

Technical efficiency is a prerequisite for economic efficiency, which in turn ensures the economic viability and sustainability of a firm. In being a useful tool to diagnose a firm's economic problems, assessment of technical efficiency has drawn broad research interest. Efficiency requires rational input allocation to achieve the desired output levels, which is important for producers who try to optimize their production decisions, and strengthens the firms' capacity to face changing market conditions, increasing input costs, economic hardships and rapid technological progress. It is also relevant for policy makers interested in enhancing firms' economic performance and competitiveness, promoting economic development and sustainable economic practices.

The analysis of technical efficiency assesses to what extent firms are able to maximize their output levels with minimum use of inputs. Since the pioneering work by Farrell (1957), the scientific community has proposed a wide array of techniques to derive firm-level efficiency measures. Two main approaches namely, parametric (Stochastic Frontier Analysis - SFA) and nonparametric approaches (Data Envelopment Analysis - DEA), have emerged as alternatives and have been extensively used in the efficiency literature (see, for a few examples, Tzouvelekas et al., 2001, 2002; Oude Lansink et al., 2002; Sipiläinen and Oude Lansink, 2005; Lohr and Park, 2006).

The assessment of a firm's performance requires the use of an adequate methodological approach to derive unbiased efficiency estimates. Several studies have shown that technical efficiency estimates are sensitive to estimation methods and functional form specifications (Ferrier and Lovell, 1990; Coelli and Perelman, 1999; Ruggiero and Vitaliano, 1999; Chakraborty et al., 2001). Inadequate representations of the production frontier and error distributions can lead to misleading results (Kumbhakar et al., 2007; Martins-Filho and Yao, 2007; Serra and Goodwin, 2009). The efficiency measurement literature has progressively evolved to incorporate new advances, refinements and extensions. This thesis focuses on a few of the most recent methodological developments.

Both parametric (SFA) and nonparametric (DEA) techniques have been shown to suffer from different shortcomings. The stochastic parametric approach addresses the main shortcomings of the deterministic approach and permits to distinguish between inefficiency and exogenous shocks that are outside the firm's control (Aigner et al., 1977; Meeusen and Van den Broeck, 1977). However, it requires specification of a parametric frontier function to capture production characteristics (e.g: Aigner et al., 1977; Meeusen and Van den Broeck, 1977). In this regard, SFA relies on two strong assumptions: the specification chosen to represent the deterministic frontier and the distributional assumption of the composite error term. In contrast, the nonparametric approach (DEA), through which all firms are compared with the "best practice" or "benchmark performance" frontier, does not rely on the definition of a functional form characterizing the underlying technology and therefore avoids misspecification problems. A disadvantage of this technique is the ignorance of the stochastic error term which implies that all deviations from the frontier are attributed to inefficiency. As a result, TE ratings obtained from the nonparametric approach are generally lower than those obtained under the parametric alternative (SFA) (Sharma et al., 1999; Puig-Junoy and Argiles, 2000; Wadud and White, 2000).

To overcome the limitations of both aforementioned approaches without foregoing their advantages, a new methodological approach based on local modeling methods has been recently proposed by Kumbhakar et al. (2007). In contrast to parametric models, this method does not require strong assumptions regarding the deterministic and stochastic components of the frontier: the parameters characterizing both production and error distribution are localized with respect to the covariates. As opposed to nonparametric approaches, local modeling methods allow for stochastic variables and variable measurement errors when estimating efficiency scores. The local modeling approach by Kumbhakar et al. (2007) is based on local maximum likelihood (LML) principles (Fan and Gijbels, 1996).

Recent advances in the efficiency literature not only refer to methodological but also conceptual issues. Traditional performance measures focus almost exclusively on the efficient use of conventional inputs and outputs. However, as the environmental sustainability of economic activities has become of increasing interest, firm-performance studies have evolved to include environmental concerns and conventional efficiency measures have been extended to include both technical and environmental dimensions. Late developments within the literature on environmental efficiency have stressed the necessity to consider the materials balance condition in order to provide sound measures of firms' environmental performance. Based on this principle, Coelli et al. (2007) suggest a new approach which, in contrast to previous modeling approaches, does not require the introduction of an extra pollution variable in the production model.

This thesis employs both local production frontier estimation techniques to derive production frontier parameters, as well as environmental efficiency measures to extend technical performance measures with environmental considerations. Its scientific contribution is both methodological and of an empirical nature, and is organized in three main core chapters that constitute three independent scientific articles. The analysis of the efficiency with which agricultural holdings operate is the guideline of this thesis. The first article uses well-known SFA techniques to conduct a comparative study of technical efficiency ratings for organic and conventional grape farms in Catalonia, Spain. The assessment of organic Spanish farms' economic viability has received scant attention by the literature and this work contributes to fill this gap. This first article is also pioneering in that it measures the contribution of farmers' preferences regarding environmental preservation and economic performance to efficiency. The analysis is conducted on cross sectional, farm-level data collected from a sample of organic and conventional Catalan farms that specialize in grape growing, and based upon a stochastic production frontier in which inefficiency effects are assumed to be a function of firm-specific characteristics.

The second article implements local estimation techniques to study efficiency of Kansas farms that specialize in the production of cereals, oilseeds and protein (COP) crops. The relevant role of Kansas in US arable crop production justifies the decision to study technical efficiency of Kansas arable crop farms. The analysis is based on farm-level data obtained from farm account records from the Kansas Farm Management Association (KFMA) dataset. In spite of the interesting features of local estimation methods, its use has been limited to a few empirical studies due to implementation complexities. Further, while the existing literature on technical efficiency has broadly compared parametric (SFA) and nonparametric approaches (DEA), no study had previously compared semiparametric techniques with mainstream methods. The second article in this dissertation sheds light on this issue.

The third research article focuses on environmental efficiency measurement of a sample of Spanish arable crop farms. Since very few proposals to measure environmental efficiency based on the materials balance principle have been proposed and empirically implemented, there is scope for significant literature contributions. The third paper builds on the proposal by Coelli et al. (2007), expands it to allow for production risk and makes a twofold contribution to the literature. To date, there are no published studies that have focused on the assessment of technical and environmental efficiency of Spanish agriculture using this methodology. Furthermore, environmental efficiency studies have failed to explicitly consider the stochastic conditions under which production takes place. We do so by implementing the recently developed state-contingent methods as proposed by Chambers and Quiggin (1998 and 2000), which represents a relevant extension to Coelli et al's (2007) proposal. To our knowledge, no previous published work has studied environmental efficiency using state-contingent methods. To the extent that the use of environmentally damaging inputs affects production risk, a model that ignores risk will produce biased efficiency estimates. The analysis is based on farm-level data collected using a questionnaire distributed among 190 Catalan arable crop agricultural holdings.

In addition to this general introduction and the concluding remarks section, this present thesis is organized into three chapters containing the three research articles summarized above. The first paper (chapter 2), entitled “The productive efficiency of organic farming: the case of grape sector in Catalonia” has been published in the *Spanish Journal of Agricultural Research*. The second paper (chapter 3), entitled “Technical efficiency of Kansas arable crop farms: a local maximum likelihood approach”, is under review in the *Agricultural Economics* journal. The third paper (chapter 4), entitled “Technical and environmental efficiency of Catalan arable crop farms”, is under review in the *Applied Economic Perspectives & Policy journal*. The final chapter synthesizes the main findings achieved in the three previous chapters. Based on these results, some policy implications as well as recommendations for future studies are derived.

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Chapter 2

The productive efficiency of organic farming: the case of grape sector in Catalonia[1]

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2.1. Introduction

Intensive agricultural systems have caused several negative externalities on humans, animals and the environment. Impacts on human health, pollution of underground and surface water, loss of biodiversity, or overutilization of natural resources are just a few examples of these externalities. Social concerns regarding the negative externalities derived from conventional agriculture have been growing. Over the last few years, there has also been an increase in consumer awareness pertaining to the consequences of food choices on their health and the environment. These concerns have led to changes in European Union (EU) agricultural policies that have progressively incorporated environmental considerations. Interest in alternative agricultural practices that are more environmentally friendly has also been growing. Organic farming, which replaces chemical inputs with organic fertilizers and non-chemical crop protection inputs, has received substantial attention within the EU.

Since the beginning of the 1990s, the EU has made a significant effort to enhance and develop organic agriculture. In order to increase the supply of organic products, EU countries have provided financial assistance for organic producers. Conversion subsidies have been introduced to compensate for the lower incomes obtained during the early stages of conversion. As a result, organic farming has quickly grown within the EU-27 countries from 0.70 million hectares in 1993 to 7.20 million hectares in 2007 (Eurostat, 2007; Willer and Kilcher, 2009). The organic area share over the total utilized agricultural area is around 4% in the EU-27, which is among the highest in the world. Organic farming in Spain has grown faster than in other EU-27 member states. While Spain ranked 10th in the EU's organic area distribution with 4,235 ha in 1991, it currently ranks second with almost one million ha (Lampkin, 1996; MARM, 2008; FiBL, 2009). Spain was the first contributor to the increase in the EU's organic area in 2006 (FiBL, 2009). The rapid and substantial increase is mainly explained by economic strategies adopted by farmers who consider organic production to be profit maximizing when accounting for subsidies received and price premiums for their produce (Armesto-López, 2008).

Despite the prominent position of Spain in the EU, the share of organic farming in the Spanish utilized agricultural area (UAA) (3.70%) is still below the EU-27 average (4%). As in Europe, more than 60% of the Spanish organic area is devoted to grassland, while arable crops are the most important organic crop with almost 275,823 ha, representing more than one third of the organic crop area. Olive groves are the second most common organic crop (22%), followed by dried fruits (15%) and grapes (7%) (MARM, 2008).

Grape is a perennial crop that, compared to other crops, has relatively low nutritional needs and adapts well to marginal soils (Winkler et al., 1974; Pongracz, 1978). This feature is considered very relevant to produce organically and makes conversion easier than for other crops. While other crops suffer many problems over the period of transition from conventional to organic, grape cultivation does not as long as the minimum level of nutrient needs is guaranteed to avoid productivity loss. These features make organic grape production a technically feasible, economically attractive and sustainable activity. Selection of resistant varieties in organic viticulture plays a vital role in ensuring high immunity against pests and diseases, high adaptation to the environmental conditions (rainfall, temperature, frost, humidity and soil quality), high productivity and profitability. Other operations are considered important to guarantee an excellent growing season for organic grape. Organic vineyard requires correct training operations to facilitate pruning (a critical practice), spraying and harvesting.

By the end of the 2000s decade, 70% of the worldwide organic grape production area was located in the EU-27, where Italy, France and Spain were the main producers. Within the EU-27, Spain represented 33% of the total (organic and conventional) vineyard area (Eurostat, 2008) and 15% of the organic vineyard area, behind Italy (32%) and France (17%). The Spanish organic grape area represented 1.70% of total grape area. In terms of production, Spain generated 23% of total grapes produced in the EU-27 and 9% of worldwide production.

Catalonia plays a significant role in organic farming in Spain, recording an average annual growth rate of 37% since 1995 (CCPAE, 2009). While the major organic producer in Spain is Andalucía (with around 60% of total area), Catalonia ranked fourth with 62,331 ha farmed by 909 producers in 2008. Further, 19% of the total Spanish organic food industry was concentrated in Catalonia. The Catalan organic vineyard area represented around 7% of the total organic grape area in Spain (being the fourth most relevant share). Since 1995, this area rapidly grew with an average annual growth of about 21%. The area increased from 207 ha in 1995 to 2,241 ha in 2008 (CCPAE, 2009). In terms of production, Catalonia contributes 7% to total Spanish vineyard production. We aim to study the technical efficiency (TE) with which Catalan grapes operate.

While conversion subsidies are useful in promoting organic conversion, they do not guarantee that converting farms will be economically viable in the future. An important first step towards economic viability is to ensure that organic production processes are technically efficient. TE is a prerequisite for economic efficiency, which is also a necessary condition for economic sustainability (Tzouvelekas et al., 2001). Knowledge about productivity and efficiency differences between conventional and organic farms is important for policy makers who are interested in promoting sustainable farming practices, farmers who try to optimize their production decisions, as well as other economic agents such as food processors and retailers who process and sell organic food. In the following lines a literature review on organic farming is presented.

The relevance of the organic farming movement has led many authors to evaluate the current situation and expectations on the future development of organic farms. Among these studies, the analyses on the adoption of organic farming practices have gained special relevance. Different methodologies, ranging from descriptive qualitative analyses to highly sophisticated econometric exercises, have served this purpose. Within the adoption literature, a first group of studies has been interested in understanding the determinants that motivate farmers to adopt the organic technology (Fairweather, 1999; Lohr and Salomonson, 2000; Pietola and Oude Lansink, 2001; Acs et al., 2007). A second group has focused on the amount of time it takes a farmer to adopt organic practices (Padel, 2001; Parra et al., 2007).

Despite the development of organic farming worldwide and especially in Europe, the literature on the TE performance of organic farming is sparse, which is mainly due to data scarcity on organic farms (Oude Lansink et al., 2002). In recent years there have been a few attempts to study this issue. Different approaches have been used to estimate the differences in TE between conventional and organic farms and different results have been derived. While some authors have utilized a parametric approach, specifically a Stochastic Frontier Analysis (SFA), others have relied on non-parametric methods, specially the Data Envelopment Analysis (DEA).

Oude Lansink et al. (2002) used DEA to compare organic and conventional crop and livestock farms in Finland and found that organic producers have higher efficiency than conventional farms (efficiency ratings for organic and conventional producers were 0.96 and 0.72, respectively), but use a less productive technology. In another recent DEA-based study, Bayramoglu and Gundogmus (2008) suggested that conventional raisin-producing households in Turkey are superior to organic producers in terms of TE (0.90 *vs.* 0.86). Both studies assumed variable returns to scale in order to compute TE.

Tzouvelekas et al. (2001; 2002a,b) used the Stochastic Production Frontier (SPF) approach to evaluate the TE ratings achieved by Greek organic and conventional farms. They found organic producers to be more efficient than conventional ones. In contrast with this finding, Madau (2007) applied a SPF model and found that Italian conventional cereal farms were significantly more efficient than organic farms (0.90 vs. 0.83). Serra and Goodwin

(2009) is the only study that compares the efficiency ratings of organic and conventional arable crop farming in Spain. In this analysis, the SPF model was estimated by a local maximum likelihood approach. Results showed that organic farms have efficiency levels that are slightly below conventional farms (0.94 *vs.* 0.97). The output-oriented measure of efficiency is the most widely used method to determine TE levels.

In spite of the recent relevant growth of organic farming in Spain, the literature on the TE of organic farming in this country is very thin. Our work contributes to the scarce literature on organic farming in Spain by carrying out a comparative study of TE ratings for organic and conventional grape farms in Catalonia. Additionally, we attempt to identify the factors that affect TE levels. SPF methodology is used for this purpose. By measuring efficiency we can assess whether economic agents use their resources optimally to reach their production objectives. Productivity differences between the two agricultural practices are also assessed by means of computing the output elasticity of different inputs and the productivity measure proposed by Kumbhakar et al. (2009).

2.2. Material and methods

The assessment of farm TE and the factors that explain TE provides valuable information to improve farm management and economic performance. In the presence of technical inefficiencies, farmers can increase their production levels without the need to increase the use of inputs that are usually scarce, or to adopt new technologies or practices. Avoiding sources of inefficiency and waste of resources is a requisite for economic sustainability. Generally, a farmer who operates with a high TE level obtains better economic results than a farmer who does not. In this regard, productive efficiency studies have important implications for economic performance, technological innovation and the overall input use in the agricultural sector.

There are two main approaches widely used in the literature to estimate TE: parametric (SFA or deterministic frontier analyses) and non-parametric methods (data envelopment analysis, DEA). Non-parametric techniques are more flexible than parametric approaches in that they can be implemented without knowing the true specification of the functional form characterizing the production technology. However, they do not allow the researcher to isolate inefficiency effects from random noise or random shocks.

To overcome the identification problem posed by non-parametric models, an alternative method can be used: SFA. This approach, that was introduced simultaneously by

Aigner et al. (1977) and Meeusen and Van den Broeck (1977), distinguishes between exogenous shocks outside the firm's control and inefficiency. Contrary to DEA and deterministic frontier analyses, SFA accounts for random noise and can be used to conduct conventional tests of hypotheses. On the other hand, SFA requires the specification of a distributional form for the inefficiency term and a functional form for the production function. Results of SFA are sensitive to these assumptions. Since agricultural production outcomes are stochastically determined due to random climatic influences, and since agricultural production studies are likely to be affected by measurement and variable omission errors (Coelli, 1995; Chakraborty et al., 2002; Oude Lansink et al., 2002), it is necessary to choose a robust model that reflects and accounts for these issues. In this regard, we select SFA as a method to correctly and consistently estimate TE.

The SPF proposed by Aigner et al. (1977) and Meeusen and Van den Broeck (1977) can be specified as:

$$y_i = f(\mathbf{X}_i;\boldsymbol{\beta})\exp(e_i);\ e_i = v_i - u_i,\ i = 1,2,...,N \tag{1}$$

where y_i denotes the level of output for the *i*-th observation (firm); $\mathbf{X}_i$ is the vector of input quantities used by the *i*-th firm in the production process; $\boldsymbol{\beta}$ is the vector of parameters to be estimated; and $f(\mathbf{X}_i;\boldsymbol{\beta})$ is a suitable functional form for the frontier. The error term e_i in equation (1) can be decomposed into two components, u_i and v_i; it is assumed that u_i and v_i are independently distributed from each other. The first component, v_i, is a standard random variable capturing the random variation in output due to statistical noise that arises from (a) the unintended omission of relevant variables from vector $\mathbf{X}_i$; (b) from measurement errors and approximation errors associated with the choice of the functional form; (c) unexpected stochastic changes in production (weather influences, for example); and (d) other factors that are not under the control of the farm. Component v_i is usually assumed to be symmetric, independent and identically distributed as $N(0,\sigma_v^2)$. The second component $u_i \sim N^+(\mu,\sigma_u^2)$, is a one-sided, non-negative random variable representing the stochastic shortfall of the *i*-th farm output from its production frontier, as a result of the existence of technical inefficiency.

The output oriented measure of TE can be expressed as the ratio of observed output to the corresponding stochastic frontier output, a measure that takes a value between 0 and 1:

$$\mathrm{TE_i} = \frac{y_i}{f(\mathbf{X}_i;\boldsymbol{\beta})\exp(v_i)} = \exp(-u_i) \quad (2)$$

Reifschneider and Stevenson (1991), Huang and Liu (1994) and Battese and Coelli (1995) proposed stochastic frontier models in which the inefficiency effects (u_i) are expressed as a linear function of explanatory variables reflecting farm socio-economic and demographic characteristics and a random error. Following Battese and Coelli (1995) we used the following TE effects model:

$$u_i = \delta_0 + \sum_{m=1}^{M} \delta_m \mathrm{Z}_{mi} + \varepsilon_i \quad (3)$$

where Z_{mi} are farm-specific variables associated with technical inefficiencies; δ_0 and δ_m are parameters to be estimated; and ε_i is a random variable with zero mean and finite variance σ_ε^2, defined by the truncation of the normal distribution such that $\varepsilon_i \geq -\left[\delta_0 + \sum_{m=1}^{M} \delta_m \mathrm{Z}_{mi}\right]$. The mean of u_i, $\mu = \delta_0 + \sum_{m=1}^{M} \delta_m \mathrm{Z}_{mi}$, is farm-specific and the variance components are assumed to be equal ($\sigma_u^2 = \sigma_\varepsilon^2$).

Following Battese and Coelli (1995), we estimate the parameters of the model defined in equations (1) and (3) by maximum likelihood procedures. The log likelihood function and the derivation of TE estimates followed the approach used in Battese and Coelli (1995). The estimation was carried out using the parameterization by Battese and Corra (1977) who replace σ_v^2 and σ_u^2 with $\sigma^2 = \sigma_u^2 + \sigma_v^2$ and $\gamma = \sigma_u^2 / (\sigma_u^2 + \sigma_v^2)$. The next section is devoted to present research results.

2.3. Results

2.3.1. Characteristics of farms and farmers

Our analysis uses cross sectional, farm-level data collected from a sample of Catalan farms that specialize in grape growing. This research focuses on Catalonia because of the important role played by the Catalan vineyard sector within the Spanish organic agriculture and the exponential growth that this sector has experienced since 1995. It is thus relevant to investigate the characteristics of this type of farming and compare them with the characteristics of the conventional sector. Data were collected by face-to-face questionnaires during the period from March to June 2008 in the major Catalan organic grape-growing areas. These areas were identified based on organic farming systems certification by the Official Certification Organism in Catalonia (Consell Català de la Producció Agrària Ecològica, CCPAE).

Geographically, our sample farms are concentrated in three different Catalan provinces (Barcelona, Tarragona and Lleida). For each organic farm, at least three neighboring conventional farms were also selected. This neighboring criterion allows for two subsamples (organic and conventional) with an analogous composition (Tzouvelekas et al., 2001; Madau, 2007). Our final sample consists of 26 organic farmers and 115 neighboring conventional farms. The following lines provide a description of sample farms both from an agronomic and economic perspective, as well as the demographic characteristics of sample farmers. Summary statistics for sample farm and farmer characteristics are presented in Table 2.1.

Based on a scale from 0 to 10, farmers were asked to grade soil quality and erosion. Although both groups have similar perceived soil quality and erosion, a large number of organic farms (53%) are located in a less favored area or in an area with specific difficulties that limit agricultural productivity (Council Regulation EC 1257/1999). In contrast, only a quarter of conventional farms are located in these areas. On average, organically farmed soil is steeper (9%) than conventionally farmed soil (3%). The difference in slope is statistically significant. Although both farm types strongly rely on rainfed agriculture, irrigation practices are relatively more important within the organic group (16% *vs.* 7%).

Land use patterns do not differ greatly between organic and conventional farms. On average 64% of conventionally cultivated land is devoted to produce grapes. Arable crops are the second most common conventional crop (19%), followed by fruits (10%) and olive groves (9%). Organic farms devote, on average, 69% of their land to grape production, mainly at the expense of arable crops that now represent 11% of cultivated land. Many different cultivars, with different abilities to withstand climatic conditions and diseases, are used within organic and conventional farms. However, both farm types use a similar range of grape varieties. The most common varieties spread among all farmers are 'Macabeu' (69.50%), 'Parellada' (58.87%), 'Ull de llebre', (42.55%), 'Xarello' (37.59%), 'Merlot' (30.50%), 'Cabernet' (22.70%) and 'Garnatxa' (18.44%).

Contrary to conventional farms that have, on average, 45 ha of agricultural land, organic farms are mainly small holdings with only 19 ha. The land tenure status is similar between farm types, with owned land representing 46% (45%) of total organic (conventional) land. Farm output is defined as the quantity of grapes produced and expressed in physical units (kg). Conventional farms' total output averages 120,364 kg, which is twice organic farms' total output (59,969 kg). However, organic farms' yields are only 16% lower than conventional farms' yields. The difference in total output and yields is statistically significant.

The average price received by organic farms more than doubles the average conventional price, suggesting statistically significant organic price premiums. The proportion that agricultural revenue represents within total farmers' revenue, which measures the degree of diversification in income sources, is 68% (77%) for organic (conventional) farms. Hence, organic farmers have more diversified income sources. Subsidies (almost 70% of organic farms receive public subsidies) and price premiums compensate for the low yields and high costs in organic farming, leading to substantially higher incomes on a per hectare basis: € 4,004 *vs.* € 2,670.

Consistent with previous research, statistically significant differences regarding input use are found between the two groups: our organic sample farms are more labor intensive than conventional farms. Both types of farms strongly rely on unpaid family labor which represents 69% (73%) of total labor in organic (conventional) farms. On a per hectare basis, expenses in fertilizers and crop protection products are much higher in organic farms (381 € ha^{-1} *vs.* 294 € ha^{-1}). Total costs per hectare are € 1,814 (€ 1,509) for organic (conventional) farms. Consistently with higher per hectare input costs borne by organic farms, this group uses 0.66 agricultural machines per hectare (machines include any farm equipment: tractors, manure spreaders, pre-pruning, cultivators, shredders, etc.), while conventional farms use 0.50 machines. Organic farmers appear to have less access to bank loans than conventional counterparts. A 50% of the latter are able to get credit, while less than 30% of the former have access to bank loans. Farmers mainly use the loans for operation and investment.

The difference between income and costs per hectare leads to profits per hectare of € 2,435 for organic farms and € 1,283 for conventional ones. Hence, organic profits per hectare almost double conventional profits. Regarding the marketing of agricultural output, both organic and conventional farms strongly rely on sales to processing companies and cooperatives. These sales represent around 71% and 73% of conventional and organic production sales, respectively. Conventional and organic farmers are members of different agricultural associations such as cooperatives, farmers' associations and syndicates, organic farming associations and protected designations of origin (PDOs). PDOs constitute the most attractive form of association: 68% and 60% of conventional and organic farmers respectively, engage with these organizations which increase the market outlets for their production.

There is a predominance of 45 years old male farmers. While organic farmers have an average of 15 years of experience managing the farm, conventional farmers have typically been managing the farm for about 18 years. Primary and unfinished secondary education is the most common educational profile characterizing both organic and conventional farmers. The family size for both groups is similar and between 3 and 4 members. Organic and conventional farmers differ in terms of their preferences[2], which helps to better understand production and adoption decisions. When it comes to production decisions, conventional farmers are more worried about farm economic performance (profit), whereas the organic group is more concerned about protecting the environment.

2.3.2. Model specification and research results

In order to study productivity and efficiency of our sample of organic and conventional Catalan grape farms, we specify our SFA as follows:

$$\ln y_i = \left(\beta_0 + \beta_0^o\right) + \sum_{j=1}^{4}\left(\beta_j + \beta_j^o.D_{c/o}\right)\ln \mathbf{X}_{ji} + \tfrac{1}{2}\sum_{j=1}^{4}\sum_{k=1}^{4}\left(\beta_{jk} + \beta_{jk}^o.D_{c/o}\right)\ln \mathbf{X}_{ji}.\ln \mathbf{X}_{ki} + \left(v_i - u_i\right) \quad (4)$$

where the subscript $i = 1, 2, ..., N$ denotes the firm number and $j, k = 1, 2, ..., J$ agricultural inputs. The dependent variable (y_i) represents grape production (in kg) by the *i*-th farm. Inputs included are: (X_1) total land devoted to grape, measured in hectares; (X_2) total labor (both hired and family labor), expressed in hours; (X_3) total amount of capital, measured as the number of machines used in the farm; and (X_4) the expenditure in fertilizers and crop protection products (in €).[3] $D_{c/o}$ is a dummy variable that reflects the agronomic technique

[2] Farmers were asked to rate their preferences for economic profit and environmental preservation from 1 to 10 (1 = not important, 10 = very important). The median of the responses is used to define a dummy variable for each type of preferences. The first dummy takes the value of 1 if the farmer rated the relevance of economic profit with the highest punctuation, *i.e.*, 10 and zero otherwise, while the second dummy is one if the punctuation was above 8.

[3] To keep the model size manageable and due to the limited number of observations available, most of the inputs considered are aggregate inputs.

(1=organic; 0=conventional). Summary statistics for the variables used in the analysis are presented in Table 2.2.

The inefficiency model is specified as $u_i = \delta_0 + \sum_{m=1}^{M} \delta_m Z_{mi} + \varepsilon_i$, with $M = 10$. The selection of Z_{mi} variables is based on previous literature, data available and our knowledge of the sector studied. Since previous research has widely shown that organic practices differ from conventional ones regarding efficiency ratings, (Z_1) is defined as a dummy variable that reflects the agronomic technique ($Z_1 = D_{c/o}$). Farmers' experience, usually included in TE studies (either as age or years of experience), is considered as the number of years dedicated to agriculture (Z_2). In line with Karagiannias et al. (2006) who shows that TE of both organic and conventional milk farms depends on specialization, the degree of specialization measured as the proportion of vineyard revenue to total agricultural revenue is reflected in (Z_3). Madau (2007) advocates that farms located in less favored areas or in mountain areas have lower TE scores than the rest. A dummy variable that indicates whether the farm is located in a less favored area or not (Z_4) is used. In line with Karagiannias et al. (2006) findings, debt is also considered through (Z_5), defined as a dummy variable equal to 1 if the farmer has financial debt and zero otherwise. Tzouvelekas et al. (2002b) conclude that organic farming subsidies tend to negatively affect efficiency levels. A dummy variable equal to 1 if the farm receives subsidies and zero otherwise is thus included (Z_6). Tzouvelekas et al. (2001) show that family-operated organic and conventional olive-growing farms tend to be less efficient than farms with strong dependence on hired labor. We thus define (Z_7) as the proportion of family labor to total labor. The two dummy variables described above that reflect farmers' preferences for economic profit and for environmental preservation (Z_8 and Z_9) are also considered. Farmers' preferences have not been used by previous literature when explaining efficiency, which represents a contribution of our analysis. The proportion of owned land to total land (Z_{10}) is also included as previous research has shown that the share of rented land is related to TE (Larsen and Foster, 2005). The model is estimated using Frontier 4.1 software (Coelli, 1996).

A series of specification tests were carried out to ensure that the model specification correctly represents our sample farms (see Table 2.3). In being a parametric approach, SFA requires specification of the functional form representing the production technology. Since this form is unknown, we have selected a flexible functional form (a translog - see equation

(4)) and compared it against another more restrictive and parsimonious specification: the Cobb-Douglas. At the 5% level of significance, we reject the null hypothesis ($H_0: \beta_{ij} = 0$), which suggests that the translog form is the suitable specification for our data. This implies that output elasticities and substitution elasticities depend on input levels. Further it also involves the relevance of input interactions when explaining production. The second test ($H_0: \delta^*_{jk} = 0$) indicates that the neutral stochastic frontier model (Huang and Liu, 1994) is the adequate representation, *i.e.*, that input use does not interfere with the variables found to explain inefficiency. Concerning the nature of the inefficiency effects, we test whether these are stochastic or not. We reject the null hypothesis ($H_0: \gamma = 0$) implying that the technical inefficiency effects are stochastic and farmers are not fully technically efficient. The fourth test ($H_0: \gamma = \delta_m = 0$) that aims to assess whether inefficiency effects are absent from the model or not, is also rejected. In addition, through the fifth test ($H_0: \delta_m = 0$), we study the influence of firm characteristics on TE levels. The null hypothesis is rejected, indicating that the variables included in the inefficiency effects equation significantly influence farms' efficiency.

Another specification test carried out concerns geographically induced differences among farms. Differences among areas not only refer to rainfall but also to winter freeze and spring frost patterns, diseases brought during hot seasons, sunlight exposure, land quality and slope, crop varieties used in different regions, etc. In order to capture these geographical differences, a set dummies representing provinces is included. Since our sample farms are concentrated in three different provinces of Catalonia (namely, Barcelona, Tarragona and Lleida), two dummies, one representing Barcelona and the other for Tarragona are included and a likelihood-ratio test is used to determine whether the two dummies are statistically different from zero. Results show that we cannot reject the null hypothesis ($H_0: D_{Barcelona}; D_{Tarragona} = 0$), which involves that the model without regional dummies in the production equation adequately fits our data. Results of the estimation of the stochastic frontier are reported in Table 2.4.

Production function results are best interpreted by means of input elasticities. Contrary to the Cobb-Douglas functional form in which coefficients have a direct interpretation as input elasticities, deriving the marginal influence of inputs on output in a translog form is not straightforward. Input elasticities are computed for our translog model as follows: $\partial \ln(Y) / \partial \ln(X_k) = \beta_k + \beta_{kk} \ln X_{ki} + \sum_{j \neq k} \beta_{kj} \ln X_{ji}$. Elasticities are computed at the data means and their standard deviations derived using the delta method (Snedecor and Cochran, 1989) (Table 2.5).

In conventional farming, land has the highest elasticity estimate. Land is followed by fertilizers and crop protection products, capital and labor. In organic farming, the highest elasticity is achieved by fertilizer and crop protection inputs. Land area and capital display similar contribution to output increases, while labor presents the lowest contribution to organic grape output.

The high elasticity of the expenditures in fertilizers and crop protection products in organic farming contrasts with the relatively low elasticity of the equivalent inputs in conventional production methods (0.69 *vs.* 0.22). This implies that grape output is more responsive to fertilizers and crop protection inputs in organic production than in conventional technology. Land area elasticity is higher in conventional farming, which is compatible with conventional yields being above organic ones. The elasticity of conventional grape output with respect to land is above one half, indicating that a 1% increase in agricultural land would lead to approximately a 0.56% increase in output. Given the restrictions faced by organic farmers to use chemical inputs, mechanical methods are likely to become relevant, which is reflected in the higher elasticity of capital in organic farms relative to conventional ones.[4] Regarding the average scale elasticity, organic farms exhibit increasing returns to scale while conventional farms operate under decreasing returns to scale. The small size of organic farms relative to conventional ones makes it especially beneficial to increase organic farm size and take advantage of economies of scale. The global productivity index proposed by Kumbhakar et al. (2009) suggests that conventional farms are, on average, 12% more productive than their organic counterparts. However, as will be seen below, the latter group of farms operates closer to their production frontier than the former.

In Table 2.4, we observe that the estimate of γ is close to one and highly significant, indicating that inefficiency effects explain most of residual variation. As noted above, ten explanatory variables are used as determinants of the inefficiency effects. Parameter estimates of the inefficiency effects model are shown in Table 2.4. Apart from adoption of organic practices, our results identify experience, family labor share in total labor, farm location and farmer environmental preferences as the variables that are more relevant in explaining technical inefficiencies. Our analysis reveals that holdings located in less-favored areas are

[4] While variable input use was collected distinguishing between grape and non-grape activities, capital was not. As a result, capital is not grape-specific. An alternative model weighting capital by the proportion of grape land on total land was estimated and results, available upon request, changed very little.

less efficient compared to the other farms. As expected, farmers with more experience tend to reach higher efficiency scores. This implies that TE increases with farmer's skills and practice. Farms that rely on a higher proportion of unpaid labor are found to be less efficient. Farms, whose manager has strong environmental preservation preferences, tend to be less efficient. Our results also show that the level of farm debt, subsidies, degree of farm specialization, tenure regimes of land and the preferences regarding economic profit do not have a significant impact on efficiency ratings. The dummy variable that reflects the agronomic technique by identifying organic farms has a negative and statistically significant sign, indicating that inefficiency decreases with the organic technology.

Technical efficiency scores for both farming methods are calculated as an output-oriented measure and results are presented in Table 2.6 with decile ranges from the computed frequency distribution. The histogram and kernel distributions of efficiency are plotted in figure 2.1. The average TE score is 80% for organic farms and 64% for conventional ones. In other words, organic (conventional) farmers reach 80% (64%) of their maximum potential output. Moreover, these TEs range from a minimum of 17% (10%) to a maximum of 100% (100%) for organic (conventional) farmers, indicating a lower dispersion in organic farming. Almost 54% of organic farmers have efficiency ratings above 90%, whereas only 16% of conventional farmers show these high performance levels. Therefore, our results indicate that if organic (conventional) farms effectively used available resources and maintained current technology, they would be able to increase their output by 20% (36%) on average. Improving TE levels can reduce production costs and improve the economic viability of farms.

2.4. Discussion and concluding remarks

The present study aims to compare technical efficiency of organic and conventional grape farms in Catalonia. Consistent with previous studies looking at the performance of organic farming (Offerman and Nieberg, 2000; Oude Lansink et al., 2002; Oude Lansink and Jensma, 2003), we find that organic farming is on average 90% more profitable, on a per hectare basis, than conventional farming. However, organic farms face higher production costs per hectare and require more labor than conventional farms. This finding is compatible with previous research on organic farming in Spain (Serra et al., 2008). Organic farms also exhibit increasing returns to scale, while conventional farms operate under decreasing returns to scale, meaning that organic farms could become more profitable with larger operations.

However, in line with previous literature (Tzouvelekas et al., 2001), conventional farmers are found to be more worried about farm economic performance (profit), whereas the organic group is more concerned about protecting the environment.

Our empirical findings suggest that organic farmers, on average, reach higher TE ratings than their conventional counterparts (80% and 64%, respectively). Our results differ from the findings by Bayramoglu and Gundogmus (2008), who assessed the efficiency of the Turkish grape sector, and are consistent with Tzouvelekas et al.'s results (2002a), who focused on the Greek grape sector. Higher efficiency scores attained by organic farms should warrant their economic viability in the agricultural sector. Several reasons may explain the higher average level of TE observed in organic farming. The higher costs per hectare supported by organic farming are likely to motivate farmers to effectively use their inputs and improve their agricultural performance. As noted by Tzouvelekas et al. (2001), information on how to adequately apply organic farming techniques may be expected to improve production performance. In this regard, the EU and national regulations concerning organic farming may help organic farmers to be more efficient relative to their conventional counterparts. Moreover, attractive organic price premiums can also explain the higher efforts by organic farms to increase TE, given the high marginal income derived from production.

An interesting finding is the high elasticity of the expenditures in fertilizers and crop protection products found in organic farming. Since organic farms cannot use non-authorized chemical fertilizers and pesticides, organic fertilizers and biological controls are important factors in organic grape production. Organic farms usually make a more rational and less arbitrary use of these inputs relative to conventional farms. A more restricted and well-managed use of these inputs contributes to explain the higher elasticity that they display in organic farming.[5]

The low elasticity of labor in both types of farms can be explained by the high share of family labor and the usual lack of qualified labor in this sector. Tzouvelekas et al. (2001, 2002a) found that family-operated farms are less efficient than farms with stronger dependence on hired labor. Larsen and Foster (2005) also suggested that the share of hired labor has a positive effect on TE for both organic and conventional farms. Another study conducted by Lambarraa et al. (2007) concluded that a higher level of inefficiency may be associated to a higher proportion of unpaid labor. More recently, Serra and Goodwin (2009),

[5] The main difference between organic and conventional farms relies on the use of chemical inputs (mainly fertilizers and pesticides), which is controlled by different regulations. The legal framework of organic farming contributes to a rational use of these inputs.

found a negative labor elasticity characterizing the conventional technology indicating an overuse of this input. The authors associated this result to the relevance of unpaid family labor in their sample of farms. As we have seen in the descriptive analysis of sample farms, organic farms are much more labor-intensive (on a per unit of land) than conventional farms. In spite of this intensive use, labor elasticity is higher in organic than in conventional farming, which is compatible with organic methods being more labor demanding than conventional practices.

Both types of farms (organic and conventional) suffer from relevant technical inefficiencies. As suggested by previous findings (Tzouvelekas et al., 2001; Madau, 2007), farms that are located in a less favored area tend to be less efficient. The finding is not surprising given the environmental and production constraints faced by the first group. A farmer who holds additional experience is more likely to have higher efficiency levels. This implies that TE increases with farmer's skills and practice. In line with the findings of Tzouvelekas et al. (2001), farms with a higher proportion of unpaid labor are found to be less efficient than farms with a stronger dependence on hired labor. Another interesting finding is adoption of organic practices can improve technical efficiency under which farmers are operating. However, organic farms show a lower productivity than conventional ones which is compatible with Oude Lansink et al. (2002) results. TE can be affected by farmers' preferences regarding the need to preserve the environment. Producers that place a higher value on preserving the environment through their production tend to be more inefficient.

Organic subsidies usually compensate organic farmers for reduced yields and adoption costs. Though subsidies have been often criticized for making economic agents less responsive to changing market conditions and increasing inefficiencies, our results show no statistically significant effect of subsidies on efficiency. There are, however, a number of things that policy makers can do to improve efficiency in grape farming. First, better promoting extension services providing detailed information to farmers may be expected to improve production performance. Second, since family labor is found to generate inefficiencies, promoting a more professionalized management of agricultural holdings by decreasing non-specialized family labor in favor of a more specialized labor force may enhance the performance of organic farming.

Improving TE allows for a reduction in production costs and increases competitiveness, which can help farmers face changing market conditions and economic hardships. Farm margins can be squeezed when market conditions change, consumers become more and more demanding and unwilling to pay higher price premiums, or middlemen in the marketing chain and retailers increase their marketing power. In this regard, improving TE can help farmers endure times of economic distress. Increasing profit levels can be achieved by means of increased organic price premiums and subsidies, or alternatively, by means of reduced production costs. A strategy based on cost reduction is especially relevant in the organic sector.

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Table 2.1. Sample farms' agronomic, economic and demographic characteristics

Variable name	Unit of measure	Organic		Conventional		T-test of mean difference Significance level[2]
		Average	SD[1]	Average	SD[1]	
Agronomic characteristics						
Total land	ha	18.90	12.82	45.33	75.68	0.00*
Proportion of land devoted to grape	%	68.48	28.49	63.48	30.43	0.43
Proportion of land devoted to arable crops	%	10.58	16.94	19.11	29.03	0.05*
Proportion of land devoted to fruits	%	10.76	18.78	10.12	14.75	0.87
Proportion of land devoted to olive groves	%	10.18	15.33	8.61	11.93	0.63
Total output	kg	59,969.04	45,217.33	120,364.27	8,2454.49	0.00*
Soil quality	(0 low, 10 high)	6.71	1.47	6.38	1.44	0.31
Erosion	(0 low, 10 high)	3.23	1.96	3.67	1.94	0.31
Soil slope	%	8.93	9.41	3.13	3.05	0.03*
Proportion of irrigated land	%	15.62	30.26	7.15	19.78	0.18
Farms in LFA[3]	(1 yes, 0 no)	0.53		0.25		0.00**
Economic, structural and other characteristics						
Output	€	33,933.52	28,062.50	36,613.27	24,474.25	0.67
Price	€ kg^{-1}	0.75	0.58	0.33	0.19	0.00*

Table 2.1. Sample farms' agronomic, economic and demographic characteristics (continued)

Variable name	Unit of measure	Organic		Conventional		T-test of mean difference Significance level
		Average	SD[1]	Average	SD[1]	
Share of agricultural income in total income	%	68.65	27.66	77.32	24.10	0.15
Share of output sold to processing companies and cooperatives	%	73.08	42.51	70.70	42.82	0.80
Proportion of owned land	%	46.31	45.81	44.56	37.94	0.86
Family labor share	%	68.85	29.71	73.02	25.48	0.51
Subsidy	(1 yes, 0 no)	0.69		0.58		0.30
Credit	(1 yes, 0 no)	0.27		0.50		0.03**
PDO[4] association	(1 yes, 0 no)	0.60		0.68		0.47
Economic profit preferences	(1=10, 0 otherwise)	0.46		0.54		0.47
Environmental preservation preferences	(1 if ≥8, 0 otherwise)	0.92		0.70		0.02**
Demographic characteristics						
Age	year	43.31	13.78	44.56	10.66	0.67
Years of experience	year	15.42	9.90	18.16	11.63	0.23
Family size	number of person	3.35	1.35	3.85	1.36	0.09
Statistics on a per hectare basis						
Yield	kg ha^{-1}	6,848.31	3,261.73	8,173.19	3,177.51	0.02*
Revenue	€ ha^{-1}	4,004.43	2,478.48	2,670.09	1,971.22	0.00*

Table 2.1. Sample farms' agronomic, economic and demographic characteristics (continued)

Variable name	Unit of measure	Organic		Conventional		T-test of mean difference Significance level
		Average	SD[1]	Average	SD[1]	
Total revenue (revenue from grape and other farm activities)	€ ha^{-1}	4,232.73	2,314.79	2,791.54	1,985.31	0.00*
Labor	hours ha^{-1}	458.93	240.41	285.76	303.34	0.00*
Machinery	N ha^{-1}	0.66	0.53	0.49	0.71	0.18
Other variable inputs (farming overheads and young vine plant expenditures)	€ ha^{-1}	860.51	751.98	834.94	1822.24	0.91
Fertilizers and crop protection	€ ha^{-1}	380.92	579.56	294.12	399.34	0.48
Total cost (specific grape production costs, farming overheads, labor costs)	€ ha^{-1}	1,813.93	1,421.67	1,508.55	1,922.69	0.38
Profit (total revenue minus total cost)	€ ha^{-1}	2,435.07	2,293.04	1,282.99	2,805.43	0.04*

[1]SD: standard deviation. [2] *,** indicate statistical significance at the 5%, and chi-square statistical significance at the 5%, respectively. [3]LFA: less favored areas. [4]PDO: protected designations of Origin.

Table 2.2. Summary statistics for the variables used in the analysis

Variable name		Unit of measure	Organic		Conventional		T-test of mean difference Significance level[2]
			Average	SD[1]	Average	SD[1]	
Output	y	kg	59,969.04	45,217.33	120,364.27	8,2454.49	0.00*
Grape land	X_1	ha	8.44	4.94	14.22	7.55	0.00*
Labor	X_2	hours	3,084.52	1,109.65	2,891.92	1,461.70	0.46
Capital	X_3	machines	4.38	2.45	4.77	2.21	0.47
Fertilizers and crop protection	X_4	€	3,520.42	6,638.52	3,776.70	3,930.05	0.85
Agronomic technique	Z_1	(1 organic, 0 non-org.)	0.18		0.82		
Experience	Z_2	year	15.42	9.90	18.16	11.63	0.23
Specialization	Z_3	%	72.19	29.76	74.41	26.43	0.73
Farms not in LFA[3]	Z_4	(1 yes, 0 no)	0.46		0.75		0.00**
Credit	Z_5	(1 yes, 0 no)	0.27		0.50		0.03**
Subsidy	Z_6	(1 yes, 0 no)	0.69		0.58		0.30
Family labor share	Z_7	%	68.85	29.71	73.02	25.48	0.51
Economic profit preferences	Z_8	(1=10, 0 otherwise)	0.46		0.54		0.47
Environmental preservation preferences	Z_9	(1 if ≥8, 0 otherwise)	0.92		0.70		0.02**
Owned land share	Z_{10}	%	46.31	45.81	44.56	37.94	0.86

[1]SD: standard deviation. [2] *,** indicate statistical significance at the 5%, and chi-square statistical significance at the 5%, respectively. [3]LFA: less favored areas.

Table 2.3. Model specification tests

Restrictions	Model	λ	$\chi^2_{0.95}$	Decision
$H_0: \beta_{ij} = 0$	Cobb-Douglas	79.76	31.41	Reject
$H_0: \delta^*_{jk} = 0$	Neutral Stochastic frontier	50.56	55.76	Accept
$H_0: \gamma = \delta_m = 0$	No inefficiency effects	31.44	20.41	Reject
$H_0: \gamma = 0$	No stochastic factor	90.27	5.14	Reject
$H_0: \delta_m = 0$	No firm- specific factors	39.90	19.67	Reject
$H_0: D_{Barcelona}; D_{Tarragona} = 0$	No regional dummies	2.00	5.99	Accept

Table 2.4. Maximum likelihood estimates for the stochastic production frontier model

Variable[1]	Parameter	Estimate	SE[2]
Frontier production function			
Constant	β_0	0.524	0.021***
Constant^o	β_0^o	-0.060	0.082
Land area	β_1	1.199	0.033***
Labor	β_2	0.080	0.043*
Capital	β_3	0.054	0.010***
Fertilizer and crop protection	β_4	-0.205	0.009***
Land area^o	β_1^o	0.335	0.186*
Labor^o	β_2^o	-0.369	0.238
Capital^o	β_3^o	0.018	0.084
Fertilizer and crop protection.^{o}	β_4^o	-0.338	0.245
(Land area) × (Land area)	β_{11}	-0.264	0.074***
(Labor) × (Labor)	β_{22}	-0.210	0.067***
(Capital) × (Capital)	β_{33}	-0.389	0.088***
(Fertilizer and crop protection) × (Fertilizer and crop protection)	β_{44}	-0.133	0.022***
(Land area) × (Labor)	β_{12}	-0.236	0.084***
(Land area) × (Capital)	β_{13}	0.535	0.104***
(Land area) × (Fertilizer and crop protection)	β_{14}	0.191	0.031***
(Labor) × (Capital)	β_{23}	-0.066	0.042
(Labor) × (Fertilizer and crop protection)	β_{24}	-0.018	0.099
(Capital) × (Fertilizer and crop protection)	β_{34}	-0.224	0.031***
(Land area) × (Land area)^o	β_{11}^o	0.628	0.189***
(Labor) × (Labor)^o	β_{22}^o	2.027	1.776
(Capital) × (Capital)^o	β_{33}^o	-0.437	0.326
(Fertilizer and crop protection) × (Fertilizer and crop protection)^o	β_{44}^o	-0.474	0.211**
(Land area) × (Labor)^o	β_{12}^o	-1.334	0.685*
(Land area) × (Capital)^o	β_{13}^o	0.563	0.231**
(Land area) × (Fertilizer and crop protection)^o	β_{14}^o	-0.043	0.099
(Labor) × (Capital)^o	β_{23}^o	-0.126	0.525
(Labor) × (Fertilizer and crop protection)^o	β_{24}^o	0.684	0.304**
(Capital) × (Fertilizer and crop protection)^o	β_{34}^o	-0.586	0.251**

Table 2.4. Maximum likelihood estimates for the stochastic production frontier model (continued)

Variable	**Parameter**	**Estimate**	**SE**[2]
Inefficiency effects model			
Constant	δ_0	-0.523	0.941
Dc/o	δ_1	-1.180	0.315***
Experience	δ_2	-0.020	0.010*
Specialization	δ_3	-0.450	0.560
Farm is not located in a less favored area	δ_4	-0.534	0.286*
Credit	δ_5	0.035	0.248
Subsidy	δ_6	0.402	0.297
Family labor share	δ_7	0.961	0.513*
Economic profit preferences	δ_8	0.007	0.260
Environmental preservation preferences	δ_9	0.712	0.285***
Owned land	δ_{10}	-0.648	0.394
$\sigma^2 = \sigma_v{}^2 + \sigma_u^2$	σ^2	0.590	0.107***
$\gamma = \sigma_u^2 / \sigma^2$	γ	0.999	4E-08***
log likelihood function			-24.607

[1] Superindex ^{o} represents the interaction of the variable with the organic farming dummy variable. [2] SE: standard error. ***, ** and * indicate statistical significance at the 1%, 5% and 10% respectively.

Table 2.5. Production and scale elasticities

Elasticities with respect to	Conventional		Organic	
	Estimate	**SE**[1]	**Estimate**	**SE**[1]
Land area	0.558	0.024***	0.323	0.138**
Labor	0.041	0.026	0.075	0.003***
Capital	0.165	0.017***	0.323	0.024***
Fertilizer and crop protection	0.219	0.028***	0.686	0.083***
Returns to scale	0.983		1.407	
Productivity differential (Kumbhakar et al., 2009)	0.12			

[1] SE: standard error. *** indicates that the parameter is significant at the 1%.

Table 2.6. Frequency distribution of technical efficiency (TE) for the conventional and organic farms

TE: Range(%)	Conventional	(%)	Organic	(%)
<20	2	1.74	1	3.85
20-30	8	6.96	2	7.69
30-40	11	9.57	0	0.00
40-50	10	8.70	0	0.00
50-60	18	15.65	2	7.69
60-70	16	13.91	1	3.85
70-80	21	18.26	5	19.23
80-90	11	9.56	1	3.85
90-100	18	15.65	14	53.84
Sample size	115	100	26	100
Mean	64.25		79.63	
SE[1]	22.64		25.68	
Minimum	9.69		17.36	
Maximum	99.99		99.98	

[1]SE: standard error

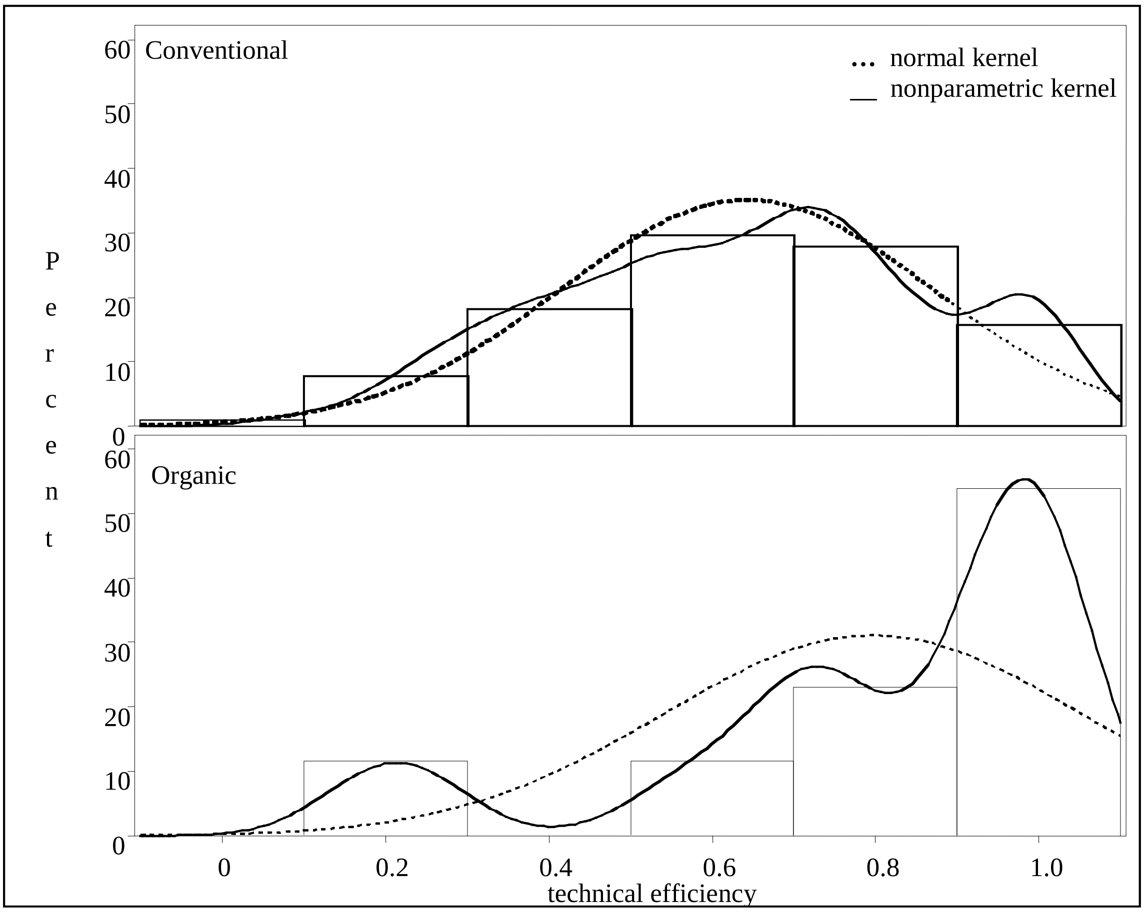

Figure 2.1. Histogram, normal and nonparametric densities of technical efficiency

Chapter 3

Technical efficiency of Kansas arable crop farms: a local maximum likelihood approach[6]

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3.1. Introduction

Technical efficiency is a prerequisite for economic efficiency, which in turn ensures the economic viability and sustainability of a firm. Assessment of firms' technical efficiency levels has drawn broad research interest. Such study is important for producers, as it assists rational input allocation to achieve desired output levels, which strengthens a firms' capacity to face changing market conditions, increasing input costs and economic hardships. It is also relevant for policy makers interested in enhancing firms' economic performance and competitiveness, and promoting economic development.

As is well known, the analysis of technical efficiency assesses to what extent firms are able to maximize their output levels with minimum use of inputs. Two main approaches have been widely used in the efficiency literature namely, parametric (Stochastic Frontier Analysis - SFA) and nonparametric approaches (Data Envelopment Analysis - DEA) (Tzouvelekas et al., 2001, 2002; Oude Lansink et al., 2002; Sipiläinen and Oude Lansink, 2005; Lohr and Park, 2006). While both encompass several advantages, they are also characterized by a number shortcomings. An important difference between these two approaches lies on the fact that the stochastic production frontier (SPF) allows for the stochastic component of production. This makes SFA suited to assess performance of production processes involving random variables. Most agricultural technologies are stochastic in nature, due to unexpected production changes resulting from weather influences and other factors that are not under the farm control. Also, agricultural production studies may be affected by measurement and variable omission errors, further emphasizing the relevance of stochastic approaches (Coelli, 1995; Chakraborty et al., 2002; Oude Lansink et al., 2002). The SFA further facilitates inference, as it permits to conduct conventional statistical tests of hypotheses. However, this approach presents important drawbacks: it relies on the assumption of a parametric functional form representing the production frontier, as well as on a distributional assumption for the random noise and inefficiency error components. Several studies show that technical efficiency results are sensitive to estimation methods and functional form specifications (Ferrier and Lovell, 1990; Coelli and Perelman, 1999; Ruggiero and Vitaliano, 1999; Chakraborty et al., 2001). Inadequate parametric representations of the frontier and the error distributions can lead to biased efficiency estimates (Kumbhakar et al., 2007; Martins-Filho and Yao 2007; Serra and Goodwin, 2009).

Nonparametric DEA techniques overcome the most relevant limitations of SFA: they do not rely on specific functional forms. However, nonparametric approaches do not allow for stochastic variables and measurement errors, which precludes separating inefficiency effects from random noise or random shocks, i.e., all production shortfalls are attributed to the inefficiency term. As a result, technical efficiency ratings obtained from the nonparametric approach (DEA) are generally lower than those obtained under the parametric alternative (SFA) (Sharma et al., 1999; Puig-Junoy and Argiles, 2000; Wadud and White, 2000). Both methods however have been found to lead to similar rankings of technical performance of decision making units (DMUs).

Recently, a new methodological approach based on local modeling methods has been developed (Kumbhakar et al., 2007) to overcome the limitations of parametric and non-parametric approaches, without foregoing their advantages. In contrast to parametric models, this method does not require strong assumptions regarding the deterministic and stochastic components of the frontier: the parameters characterizing both production and error distribution are allowed to depend on the covariates through a process of localization. As opposed to nonparametric approaches, local modeling methods allow for stochastic variables and variable measurement errors when estimating technical efficiency scores. Furthermore, these techniques accommodate the heterogeneity in the data by deriving observation-specific variances of the inefficiency and noise components of the error term (Serra and Goodwin, 2009). The local modeling approach by Kumbhakar et al. (2007) is based on local maximum likelihood (LML) principles (Fan and Gijbels, 1996).

In spite of the interesting features of this approach, the complexity of implementing the method has limited its use to a few empirical studies.[7] The work by Serra and Goodwin (2009) constitutes a notable exception. The present study focuses on estimating technical efficiency ratings of a sample of cereals, oilseeds and protein crop (COP) farms in Kansas using flexible LML methods that are compared with the results of DEA and SFA techniques. Our article contributes to the scarce literature on the use of local modeling techniques to assess technical efficiency. While the existing literature on technical efficiency has broadly compared parametric (SFA) and nonparametric (DEA) approaches, to date, there is no study that compares technical efficiency scores under DEA, SFA and LML. In addition, ours constitutes the first study that assesses the efficiency of Kansas arable crop farms using local modeling approaches (Rowland et al., 1998; Cotton et al., 1999; Serra et al., 2008). The relevance of Kansas as a leading US producer of arable crops makes the analysis especially interesting. In 2010, Kansas generated almost 20% and 50% of total wheat and sorghum

[7] The software code to estimate the model is available upon request.

produced in the US, respectively. Kansas is also a leading corn and soybean producer, with around 5% of the global US production. The relevant role of Kansas in US arable crop production justifies our decision to study technical efficiency of Kansas arable crop farms.

The paper is organized as follows. In the next section we describe the methodology used in our empirical analysis. The third section presents the data and results from the empirical implementation. We finish the paper with concluding remarks.

3.2. Methodology

Several approaches have been used in the literature to assess firm-level performance. SFA and the DEA constitute two mainstream techniques that have their intrinsic drawbacks and advantages. One attractive advantage of the nonparametric DEA is that it does not require an aprioristic specification of the frontier functional form and error distribution. However, DEA methods ignore the stochastic component of production that may arise from unobserved heterogeneity and measurement errors. This may lead to biased and misleading technical efficiency measures. While this problem is addressed by the SFA, the major drawback of the latter is that it relies on strong assumptions regarding specification of the production frontier and the error distribution. The parametric approach is thus likely to be influenced by misspecification issues and yield biased efficiency estimates. These shortcomings have been widely discussed in the technical efficiency literature and several methodological improvements have been proposed.

The nonparametric techniques by Cazals et al. (2002), Aragon et al. (2005), or Daouia and Simar (2007) are robust to outliers, but still rely on the so called “deterministic” assumption intrinsic of DEA (Kuosmanen et al., 2009). Kuosmanen (2006) proposed another approach namely Stochastic Nonparametric Envelopment of Data (StoNED) which allows combining stochastic frontier and a deterministic, nonparametric approach. However, this method still requires a priori assumptions on inefficiency and noise distribution. The same limitation can be attributed to Fan et al. (1996), who proposed a semiparametric method based on a two-step pseudo-likelihood estimator. An alternative technique recently proposed by Kumbhakar et al. (2007) overcomes the limitations of SFA and DEA, without foregoing their advantages. Based on the LML principle proposed by Fan and Gijbels (1996), this new approach localizes the parameters of the stochastic and the deterministic components of the frontier model (flexibilized) with respect to the covariates.

Since our analysis is based on a large number of Kansas farms over a broad geographic region with different climatic conditions, heterogeneity is likely to characterize the sample (different farm sizes, uneven skills, etc). The LML approach is suited to deal with heteroscedasticity in both noise and inefficiency, as it localizes the standard errors characterizing the distribution of efficiency and noise components of the error term. Based on this approach, we seek to assess the technical efficiency with which COP Kansas farms operate and compare efficiency ratings with scores derived from the DEA and SFA alternatives. In the following lines, a description of the theoretical framework of the LML stochastic frontier is presented.

The stochastic frontier models proposed by Aigner et al. (1977) and Meeusen and Van den Broeck (1977) can be specified as follows $Y_i = \beta_0 + \beta^T X_i - u_i + v_i$, where Y_i and X_i are independent and identically distributed random variables. Y_i represents output produced by firm $i = 1,...,N$ and the vector representing input use is $X_i \in \mathbb{R}^d$. The betas are unknown parameters. As usual, the stochastic frontier has a composite error term, $-u_i + v_i$, where $u_i > 0$ is the inefficiency term and v_i is the random noise term. The parametric estimation of stochastic frontier models requires definition of the joint probability density function (pdf) of (Y, X), which is decomposed into a marginal pdf for X, $pdf(x) = p(x)$ and a conditional pdf for Y given x, $pdf(y \mid x) = g(y, \theta(x))$, where $\theta(x) \in \mathbb{R}^k$ is the localized vector of parameters to be estimated, and g is a function assumed to be known.

The LML is built upon the anchorage parametric model proposed by Aigner et al. (1977). The conditional pdf for Y given $X = x$ is defined as: $Y = r(X) - u + v$. Following Kumbhakar et al. (2007), the inefficiency term u is assumed to follow a half normal distribution $\left(u \mid X = x \sim \left|N\left(0, \sigma_u^2(x)\right)\right|\right)$, the error term v is assumed to have a normal distribution $(v \mid X = x \sim N(0, \sigma_v^2(x)))$ and u and v are assumed to be independently distributed, conditional on X. The local polynomial approximation is used to estimate the three dimensional local parameter vector $\theta(x) = \left(r(x), \sigma_u^2(x), \sigma_v^2(x)\right)^T$. The conditional log-likelihood function is written as $L(\theta) = \sum_{i=1}^{N} \log g\left(Y_i, \theta(X_i)\right)$ and can be locally approximated using an *m*th order local polynomial fit:

$$L_N\left(\theta_0,\theta_1,...,\theta_m\right)=\sum_{i=1}^{N}\log g\left(Y_i,\theta_0+\theta_1\left(X_i-x\right)+...+\theta_m\left(X_i-x\right)^m\right)K_H\left(X_i-x\right) \quad (1)$$

where x represents a fixed interior point in the support of the pdf $p(x)$, $\theta_j=\left(\theta_{j1},...,\theta_{jk}\right)^T$ for $j=0,1,...,m$, and $K_H\left(u\right)=\left|H\right|^{-1}K\left(H^{-1}u\right)$, being K a multivariate kernel function and H a positive definite and symmetric bandwidth matrix. The local polynomial estimator $\hat{\theta}(x)$ is given by $\hat{\theta}(x)=\hat{\theta}_0\left(x\right)$ where

$$\left(\hat{\theta}_0\left(x\right),...,\hat{\theta}_m\left(x\right)\right)=\arg\max_{\theta_0,...,\theta_m}L_N\left(\theta_0,\theta_1,...,\theta_m\right) \quad (2)$$

The LML estimator can be derived using a local linear fit (Kumbhakar et al., 2007). To do so, the random noise and inefficiency components are assumed to follow a local normal and a half normal distribution, respectively. The conditional pdf of $\varepsilon=v-u$ is specified as:

$$f\left(\varepsilon \mid X=x\right)=\frac{2}{\sigma(x)}\varphi\left(\frac{\varepsilon}{\sigma(x)}\right)\Phi\left(-\varepsilon\frac{\lambda(x)}{\sigma(x)}\right), \quad (3)$$

where $\sigma^2\left(x\right)=\sigma_u^2\left(x\right)+\sigma_v^2\left(x\right)$, $\lambda(x)=\sigma_u\left(x\right)/\sigma_v\left(x\right)$ and $\varphi(.)$ and $\Phi(.)$ represent the probability and the cumulative distribution functions of a standard normal variable, respectively. The local linear parameter is given by $\theta(x)=\left(r\left(x\right),\sigma^2\left(x\right),\lambda\left(x\right)\right)^T$ and the conditional pdf of Y given X is expressed as:

$$g\left(y;\theta(x)\right)=\frac{2}{\sigma(x)}\varphi\left(\frac{y-r(x)}{\sigma(x)}\right)\Phi\left(-\left(y-r\left(x\right)\right)\frac{\lambda(x)}{\sigma(x)}\right) \quad (4)$$

Therefore, the approximation of the conditional local log-likelihood function is specified as:

$$L(\theta)\propto\sum_{i=1}^{N}-\frac{1}{2}\log\sigma^2\left(X_i\right)-\frac{1}{2}\frac{\left(Y_i-r\left(X_i\right)\right)^2}{\sigma^2\left(X_i\right)}+\log\Phi\left(-\left(Y_i-r\left(X_i\right)\right)\frac{\lambda\left(X_i\right)}{\sqrt{\sigma^2\left(X_i\right)}}\right) \quad (5)$$

In the present study, a local linear model for the frontier $r\left(x_i\right)$ and a local constant model for the parameters of the error term is used that allows rewriting expression (5) as:

$$L_N\left(\theta_0,\Theta_1\right)\propto\sum_{i=1}^{N}\left[-\frac{1}{2}\log\sigma_0^2-\frac{1}{2}\frac{\left(Y_i-r_0-r_1^T\left(X_i-x\right)\right)^2}{\sigma_0^2}+\log\Phi\left(-\left(Y_i-r_0-r_1^T\left(X_i-x\right)\right)\frac{\lambda_0}{\sqrt{\sigma_0^2}}\right)\right]K_H\left(X_i-x\right) \quad (6)$$

where $\theta_0=\left(r_0,\sigma_0^2,\lambda_0\right)^T$ and $\Theta_1=r_1^T$. The local linear estimator of the model is given by $\hat{\theta}_0$:

$$\left(\hat{\theta}_0\left(x\right),...,\hat{\Theta}_1\left(x\right)\right)=\arg\max_{\theta_0,\Theta_1}L_N\left(\theta_0,\Theta_1\right). \quad (7)$$

The local likelihood function (6) does not differ substantially from the conventional likelihood function used in SFA (8). Observations in the former are weighted using the multivariate kernel function (K_H).

$$Ln\ L=-\frac{1}{2}\log\sigma_0^2-\frac{1}{2\sigma_0^2}\sum_{i=1}^{N}\varepsilon_i^2+\sum_{i=1}^{N}\log\Phi\left(-\frac{\varepsilon_i\lambda_0}{\sigma_0^2}\right) \quad (8)$$

The choice of the order of the local polynomial being fit may affect the quality and robustness of the estimation. There exists a trade-off between bias and variance. While higher order fits may be used with the purpose of reducing bias, variance in estimates may increase which may lead to numerical instability. This is not optimal in the sense of minimizing the kernel function, promoting the efficiency of the estimates and selecting the true bandwidth (Cleveland and Loader, 1996; Hengartner et al., 2002; De Brabanter et al., 2013). Further, as explained by Fan and Gijbels (1996), since the modeling bias is primarily controlled by the bandwidth, the order of the local polynomial is less crucial. As a result, Fan and Gijbels (1996) recommend the use of the lowest odd order polynomial determined as $p=\nu+1$, where ν represents the order of the derivative required, or occasionally $p=\nu+3$. Hall and Racine (2013) and Fan and Gijbels (1996) consider local linear regressions as one of the best bias correction methods, specially in the boundary areas. Furthermore, several authors prefer to choose a polynomial of order $p=1$ for computational ease considerations (Cleveland, 1979; Heij et al., 2004; Wu and Zhang, 2006; Hassouneh et al., 2012).

As noted above, LML allows deriving observation-specific estimates taking into account the heterogeneity in inefficiency and noise terms. Following Jondrow et al. (1982), the efficiency measure for a particular point can be obtained from the following expression:

$$\hat{u}_i = \frac{\hat{\sigma}_0(X_i)\hat{\lambda}_0(X_i)}{1+\hat{\lambda}_0^2(X_i)}\left[\frac{\varphi\left(-\hat{\varepsilon}(X_i)\hat{\lambda}_0(X_i)/\hat{\sigma}_0(X_i)\right)}{\Phi\left(-\hat{\varepsilon}(X_i)\hat{\lambda}_0(X_i)/\hat{\sigma}_0(X_i)\right)} - \frac{\hat{\varepsilon}(X_i)\hat{\lambda}_0(X_i)}{\hat{\sigma}_0(X_i)}\right] \tag{9}$$

where $\hat{\varepsilon}(X_i) = Y_i - \hat{r}_0(X_i)$. In the case of variables measured in logs, the efficiency score is given by $\hat{eff}_i = \exp(-\hat{u}_i) \in [0,1]$. Since LML allows deriving local parameter estimates based on kernel regression, each farm's reference set is more homogeneous relative to other alternative efficiency-measurement techniques, which is likely to lead to higher efficiency levels.

Finding a solution to the maximization problem in (7) requires specifying starting values. To do so, we follow Kumbhakar et al. (2007) and start with the local linear least squares estimator of $\hat{r}_0(x)$ and $\hat{r}_1(x)$ and the SFA estimators of $\hat{\sigma}^2$ and λ. The local intercept $\hat{r}_0(x)$ is corrected for the moment condition along the lines of the parametric Modified Ordinary Least Squares (MOLS) estimator. Kumbhakar et al. (2007) recommend using the following expression for such purpose $\hat{r}_0^{MOLS}(x) = \hat{r}_0(x) + \sqrt{2\hat{\sigma}_u^2/\pi}$, where $\hat{\sigma}_u^2 = \hat{\sigma}^2\hat{\lambda}^2 / \left(1+\hat{\lambda}^2\right)$. Hence, initial values for solving (7) are obtained from $\theta_0 = \left(\hat{r}_0^{MOLS}, \hat{\sigma}^2, \hat{\lambda}\right)^T$ and $\Theta_1 = \hat{r}_1(x)^T$.

The product kernel chosen is $h^{-d}\prod_{j=1}^{d} = K\left(h^{-1}(x_j)\right)$, where $K(.)$ represents the Epanechnikov Kernel and d represents the number of covariates. Fan (1993) suggested that using the Epanechnikov Kernel maximizes estimated efficiency. The bandwidth is adjusted for different variable scales and sample sizes and is defined as: $h = h_{base}s_x N^{-1/5}$; where s_x represents the vector of empirical standard deviations of the covariates and N represents the number of observations. The choice of the optimal value for h_{base} is based on the cross validation criterion (CV) proposed by Kumbhakar et al. (2007). The CV, for a given value of h_{base}, is computed by minimizing the following expression:

$$CV\left(h_{base}\right)=\frac{1}{N}\sum_{i=1}^{N}\left[\left(Y_i-\left(\hat{r}_0^{(i)}\left(x\right)-u_i^{(i)}\right)\right)\right]^2, \tag{10}$$

where $\hat{r}_0^{(i)}$ and $u_i^{(i)}$ are the leave-one-out versions of the local linear estimators defined above. The cross-validation procedure, which involves estimating the model several times, leaving one unit out at a time, allows controlling for the unobserved characteristics of observations which in turn ensures the efficiency of estimates (Beck, 2001).

As noted above, apart from Kumbakar et al.'s (2007) LML proposal, efficiency of Kansas farms is also assessed by DEA and SFA approaches. The random parameter approach is used to derive SFA estimates. Following Greene (2002), the simulated log-likelihood function assuming normal and half normal distributions can be defined as:

$$Ln\ L_S=\sum_{i=1}^{N}\frac{1}{R}\sum_{r=1}^{R}\log\frac{1}{\sqrt{2\pi}}+\log\Phi\left(\frac{[\mu_i/\lambda]\pm[(Y_{it}-\beta_{ir}X_{it})\lambda]}{\sqrt{\sigma_u^2+\sigma_v^2}}\right)-\log\Phi\left[\frac{\mu_i}{\sigma_u}\right]-\frac{1}{2}\log\sigma^2-\frac{\left(\mu_i\pm(Y_{it}-\beta_{ir}X_{it})\right)^2}{2\sigma^2} \tag{11}$$

where r represents the number of replications and t indicates time period. The DEA linear programming model can be expressed as (Färe et al., 1994):

$$\begin{aligned}&\max_{\phi,\lambda}\phi\\&s.t.\\&-\phi y_i+Y\lambda\geq 0\\&x_i-X\lambda\geq 0\\&N1'\lambda=1\\&\lambda\geq 0\end{aligned} \tag{12}$$

where $1\leq\phi<\infty$, N is the number of farms, X is a $d\times N$ matrix of inputs, Y is a $1\times N$ matrix of outputs. Technical efficiency scores are given by $1/\phi$. The constraint $N1'\lambda=1$ is included to allow for variable returns to scale (VRS). As is well known, without such constraint, constant returns to scale (CRS) are assumed (Charnes et al., 1994). To test for divergence between the efficiency distributions obtained from LML, SFA and DEA methods, the standard Kolmogorov-Smirnov (KS) two-sample (two-tail) test statistic is conducted:

$$D = \max \left| F^{a}(x,N) - F^{b}(x,N) \right| \tag{13}$$

where $F^{a}(x,N)$ represents the empirical distribution function for a sample a with total observations N.

3.3. Data and results

3.3.1. Data

The empirical application focuses on a sample of Kansas farms that specialize in the production of COP crops. Farm-level data are obtained from farm account records from the Kansas Farm Management Association (KFMA) dataset and cover the period 2000-2010. Data available include farm production and input use, financial and socio-economic characteristics, as well as farm structural characteristics. To ensure that COP is the main farm output, farms whose COP sales represent at least 90% of total farm income were selected. This criterion allows obtaining a relatively homogeneous sample of farms. The dataset is an unbalanced panel that contains 1,258 observations.

We define farm output (y_i) as an implicit quantity index that is computed as the ratio of production in currency units to the output price index. Since information on market prices is unavailable at the farm-level, a Paasche price index is built on the basis of state-level cash unit prices and production data. Output y_i includes the predominant crops in Kansas (Albright, 2002): wheat, corn, soybean and sorghum. The inputs considered as explanatory variables are COP land (x_1) measured in acres, total labor input (x_2), mainly composed of family labor, and expressed in annual working units (AWUs), as a fraction of 10-hours per day, chemical inputs (x_3), other inputs (x_4) and capital (x_5). Chemical inputs are defined as a quantity index that includes the use of fertilizers and pesticides, and is obtained by dividing input expenditures by its corresponding price index. Other inputs, also defined as a quantity index, include fuel and seed expenses. Capital input (x_5) aggregates the value of machinery, other equipment and buildings used in the production process, and is determined by dividing capital value by its corresponding price index. Input prices are measured using national input price indices. Monetary values are measured at constant 2000 prices. Data unavailable from the Kansas database include country-level input price indices and state-level output prices and quantities and are obtained from the United States Department of Agriculture (USDA) and the National Agricultural Statistics Service (NASS).

Table 3.1 provides summary statistics for the variables used in the analysis. Sample farms use, on average, 293 AWUs, of which 82% represents unpaid family labor. In contrast to the European Union (EU) arable crop farms that are mainly small holdings with around 116 acres (Farm Accountancy Data Network, FADN 2012), Kansas farms devote 1,278 acres on average to COP production. More than 80% of the COP area is allocated to wheat, soybeans, sorghum and corn production. The average value of farm production (around 154 thousand dollars) almost doubles the EU value (about 84 thousand dollars). However, per acre statistics suggest that EU farms are much more intensive than Kansas farms: while EU farms have an average income of 441 dollars per acre, Kansas income is 122 dollars per acre. Sample farms' investments in machinery and buildings are on the order of 163 thousand dollars. On per acre basis, Kansas farms are less intensive in capital use (150 dollars per acre) relative to the EU farms with investment ratios on the order of 1,666 dollars per acre (FADN, 2012). To ensure immunity against pests and diseases and to avoid productivity loss due to pest infestations, Kansas farmers spend around 38 thousand dollars annually on chemical inputs. On a per acre basis, expenses in fertilizers and crop protection products are much higher in EU farms (178 dollars per acre versus 29 dollars per acre). Expenses in other inputs, seeds and energy is rather low compared to chemical input costs, and on the order of 24 thousand dollars.

3.3.2. Empirical results

Using the aforementioned variables and following Kumbhakar et al. (2007), we specify the anchorage parametric model as a Cobb-Douglas function:

$$\log Y = \beta_0 + \sum_{j=1}^{5} \beta_j \log X_j - u + v \tag{14}$$

It is relevant to note that rigidities associated to this production frontier are overcome by estimating the frontier for each observation in the sample, i.e., flexibility is achieved through varying parameter estimates. To select the bandwidth required to derive the LML estimator of

(14), we use the CV procedure described above. It is worth noting that with multiplicative multivariate kernels, an observation i will only be considered in the LML estimation if all covariates x_i fall into the interval $\left[x_i - h_i, x_i + h_i\right)$; where $h_i = h_{base} s_{x_i} N^{-1/5}$. If even one of the components fails to fall into this interval, the observation will not be considered for the estimation. Such procedure requires relatively large values for h_{base} in order to have a sufficiently large subsample of observations to locally estimate the stochastic production frontier.[8] The more important the sample heterogeneity is, the bigger the required bandwidth. We start with a crude grid of values to then focus on a finer grid for the selection of the optimal h_{base} according to (10). Final results show that at the optimal $h_{base} = 11$, the bandwidths h_1, h_2, h_3, h_4 and h_5 take values of 2.38, 2.34, 3.37, 3.47 and 2.86, respectively. The number of observations at each data point is, on average, is 1,041. The distribution of the number of observations at each data point is presented in figure 3.1 below. Once we select the adequate bandwidth for our data, we then derive local parameter estimates. [9]

Descriptive statistics for the variation of local estimates of σ_u^2 and σ_v^2 are shown in table 3.2. These statistics confirm the presence of heteroscedasticity and indicate an important degree of variation among observations regarding the shares of the inefficiency term to the noise term ($\lambda = \sigma_u^2 / \sigma_v^2$). Figure 3.2 illustrates the variation of the parameters of the deterministic component of the frontier. Since we use a Cobb–Douglas functional form, coefficients represent input elasticities. Variation of the localized estimates suggests that assuming the same input elasticities for all observations may not be reliable. Variation is specially relevant for land, with an elasticity that ranges from 19% to 43%, followed by chemical inputs, labor and capital, that have an elasticity fluctuating from 26% to 42%, 2% to 14% and 21% to 33%, respectively. Input elasticities indicate that the average farm operates under constant returns to scale with a mean scale elasticity equal to 1.005 and a standard deviation of 0.089.

[8] A minimum of 9 observations is required and this was imposed.

[9] The monotonicity condition of production functions implies that production should monotonically increase in all inputs, and is certainly an important concept in efficiency analyses (Henningsen and Henning, 2009). While DEA implicitly imposes monotoncity, we impose it in SFA and LML techniques. Technical efficiency measurement generally assumes that producers maximize output given input quantities, but not that producers maximize their profit. Thus, in contrast to monotonicity, there is not necessarily a technical motivation for a production function to be quasi-concave (Henningsen and Henning, 2009).

Production elasticity estimates show, on average, that chemical input use has the highest potential to increase output, followed by land, capital, other inputs and labor (table 3.3). The low contribution of labor to farm production increases can be attributed to the high share of family labor. Since this labor type usually involves an opportunity cost but not an actual cost, incentives to use it efficiently may be weaker than for other inputs. The fact that capital, land and other inputs have lower elasticities than chemicals suggests that the latter are used less intensively. Input cost shares can be used as a reference for estimated elasticities. Under perfect competition and constant returns to scale assumptions, output elasticity with respect to input should equal the input cost share (Shumway and Talpaz, 1980; Krishnapillai and Thompson, 2012). Table 3.3 shows that there is no substantial difference between shares and elasticities, which provides supporting evidence of the reasonability of our findings, i.e., our empirical findings suggest that Kansas farms are likely to be operating under perfect competition and constant returns to scale.

Small differences between estimated output production elasticities of inputs and observed factor shares can be attributed to production spillovers, excess returns, omitted variables, or measurement errors (Stiroh, 2002). Average estimated elasticities of chemical inputs (0.293), other inputs (0.199) and labor (0.048) are slightly below average factor shares (0.334, 0.241, 0.053, respectively). In contrast, land area and capital input elasticities are higher than factor shares (0.248 and 0.217 vs. 0.173 and 0.197, respectively). This suggests that land and capital productivity outweighs marginal costs and that these two inputs are under-used.

Table 3.4 illustrates the distribution of LML efficiency estimates. The same table also presents the distribution under the alternative DEA and SFA approaches. A translog production function[10] is defined as the anchorage model for SFA (equation 15), which is estimated using the random parameter technique.

$$\log Y = \beta_0 + \sum_{j=1}^{5} \beta_j \log X_j + \tfrac{1}{2} \sum_{j=1}^{5} \sum_{k=1}^{5} \beta_{jk} \log X_j \log X_k - u + v \tag{15}$$

Localized technical efficiency estimates show a high average score, on the order of 0.905, indicating that farmers reach about 91% of their maximum potential output. Therefore, our

[10] To economize space, parameter estimates of the translog are not presented. However, results are available upon request.

sample farms could increase their output by a further 9% by simply using their inputs more efficiently, without incurring extra input costs or adopting new technologies. In the presence of inefficiencies, the use of existing technologies is more cost effective as a means to improve output than adopting new technologies (Shapiro, 1977; Belbase and Grabowski, 1985).

Average DEA-CRS efficiency scores (0.808) are lower than LML ratings. Under VRS, however, efficiency evaluations are much closer to LML results (0.917).[11] Average SFA technical efficiency scores (0.804) are also below LML scores. At the 5% level of significance, the KS test indicates that DEA and SFA score distributions differ from LML's (table 3.5). Given the fact that LML overcomes the most relevant limitations of DEA and SFA methods, its robustness should be higher.[12] Reliable information about farm efficiency performance is relevant to identify inefficient farms and define adequate policy and management strategies. Defining these strategies based on DEA or SFA estimates, may lead to targeting the wrong farms, while overlooking inefficient farms that need to improve their performance levels. As shown in table 3.4, more than a half and 40% of Kansas farms are assigned efficiency scores below 80% when using DEA-CRS and SFA estimates, respectively, while only 6% of total observations exhibit this performance under LML. Hence, both DEA-CRS and SFA approaches are likely to overestimate inefficiency.

In the following lines, we compare the results derived in our analysis with findings by previous research. Following Balcombe et al. (2006), the purpose of this comparison is to check the confidence and robustness of our findings, i.e., whether they concur or not with other results derived from different methods and whether they are or not within the range of existing estimates in the literature. Our results differ from those in Serra et al. (2008) who used the same database, but focused on the period 1998-2001. Through Kumbhakar's stochastic frontier model (2002), Serra et al. (2008) obtained mean technical inefficiency levels of 0.30, versus 0.09 in our analysis. The use of different methodologies or farmers' performance improvement over time can explain differences in efficiency scores across studies. However, our results are closer to other findings by Rowland et al. (1998) for a sample of Kansas swine operations from 1992 through 1994, or Cotton et al. (1999), for a sample of multi-output Kansas farms during the period 1985 to 1994. Both authors used

[11] DEA results suggest that Kansas farms do not operate at optimal scale.

[12] Robustness assessment requires simulation exercises. Kumbhakar et al. (2007) show how LML outperforms parametric frontier methods in a number of situations and conclude that LML should always be preferred to traditional MLE techniques with anchorage models. Formal comparison (robustness assessment) between DEA and LML has not been conducted, which offers scope for future research.

nonparametric DEA techniques to derive efficiency estimates and obtained mean efficiency scores of 0.89 and 0.91, respectively.

Under the LML approach, technical efficiencies range from a minimum of 0.095 to a maximum of one, indicating important dispersion and heterogeneity within Kansas farms. Using LML technical efficiency levels to identify cluster membership, cluster analysis classifies Kansas farms into three distinct groups. In order to characterize the groups, differences in farm and farmer characteristics across clusters are assessed using anova and cross tabulation analyses, depending on the quantitative or categorical nature of the data. These characteristics include farm size (categorically defined through three dummy variables representing farms that cultivate less than 500 acres, between 500 and 1000 acres, and more than 1000 acres); proportion of irrigated land (share of irrigated land to total land); rented land share (proportion of rented land to total land); unpaid labor share (proportion of family labor to total labor); farm output (defined as a quantity index as explained above) and yields; farm manager age; education expenses; public subsidies and non-agricultural income measured in dollars. Results of this analysis are presented in table 3.6. On average, the first, second and third groups have an efficiency level of 0.78, 0.88 and 0.96, respectively.

Anova and cross tabulation analysis results (table 3.6) show that increased farm size, measured as the extension of cultivated land, brings higher efficiency, which is compatible with the presence of increasing returns to scale in small farms. Farm size differences across efficiency groups are statistically significant and lead to different output indices and yields. Efficiency is further positively related to output and yields, being differences across groups statistically significant.

Although all farm types strongly rely on rainfed agriculture, irrigation practices are relatively more important among medium and high efficiency groups. While all three farm types mainly use unpaid family labor, a higher relevance of family labor is associated to poorer performance. Hence, it seems that actual costs of paid labor exert a positive influence on farm performance, relative to the opportunity costs of unpaid workforce. Along the same lines, those farms with better efficiency levels are the ones that can afford higher land rental costs.

Farmers with higher education expenses tend to be more efficient. However, the difference across groups is not statistically significant. An interesting finding is that younger farmers are likely to be more technically efficient. Subsidies received from government differ across clusters and have a positive relationship with efficiency, which may be due to the fact that subsidies are paid based on farm size. Non-agricultural activities show a significant negative relationship with efficiency, suggesting that farmers who diversify their income sources by conducting off-farm activities tend to be less efficient.

Improving efficiency performance may require actions at the farm, policy and academic levels. Academically, further research could be conducted so as to identify additional inefficiency causes, as well as their marginal impact on efficiency. Those elements with higher marginal impacts on efficiency should be the ones receiving further attention by farm managers and policy makers. Refined methods including risk and risk attitudes may allow more accurate efficiency estimates. We find evidence that higher education and professionalized labor force may lead to higher efficiency. As a result, any action aimed at promoting high-quality and skilled work is likely to increase farms' economic sustainability. At the policy level this could be achieved through information campaigns and extension services. Similar results should be obtained through skilled labor force development initiatives adopted by the farm manager (education and training actions). Efficiency is also positively related to a farm's size. Increased farm size may be pursued through land acquisitions and rental. To the extent that land market rigidities are relevant, land rental may offer a flexible alternative that may even result in higher profits than purchasing own land (actual rental costs induce higher efficiency relative to the opportunity costs of own land). Adopting irrigation practices or promoting farm specialization constitute other efficiency improving alternatives. Generational change in farming may also prove to be very useful.

3.4. Concluding remarks

The relevance of deriving reliable technical efficiency scores to assist firms' management decisions as well as policy design, makes it essential to use methodologies that produce farm-level non-biased efficiency ratings. The parametric SFA and the nonparametric DEA approaches have focused the attention of mainstream efficiency literature. Both approaches have been widely criticized for their shortcomings that may lead to biased efficiency estimates.

Recently, Kumbhakar et al. (2007) proposed a new approach, namely the LML method. The method estimates the parameters of the deterministic and stochastic components of the frontier locally. LML methods overcome the shortcomings of SFA and DEA without foregoing their advantages. However, some of the major drawbacks of this approach are the "curse of dimensionality" and the estimation convergence issues that are likely to arise. These drawbacks do not allow estimating too many parameters, thus restricting the alternative functional forms that can be considered. In any case, rigidities associated to simple production function specifications are overcome through varying parameter estimates. Another LML limitation is the selection of the order of the local polynomial, as there is a trade-off between bias and variance of the estimation. High order polynomials will reduce the bias, but at the cost of the variance of fitting. In spite of the complexity of this approach, it is highly recommended to derive reliable and unbiased estimates. LML techniques are used in this article to assess the efficiency levels achieved by Kansas farms specialized in cereals, oilseeds and protein crop production and compares them with those obtained from DEA and SFA models. Farm-level data obtained from farm account records from the KFMA dataset covering the period 2000-2010 are used.

Empirical results support the relevance of using the LML approach through the variation in the localized parameter estimates, representing the variance of the composite error term and input elasticities. Results show high mean efficiency scores (0.905) indicating that farmers could increase their output by 9% keeping their input bundle constant. Technical efficiency scores derived from the LML approach are higher than those of the DEA-CRS and SFA models, but close to DEA-VRS ratings. According to the KS test, the efficiency score distributions obtained from DEA and SFA differ from LML distribution ratings. Since LML allows both for stochastic error terms, as well as for flexibility in the functional form representing the frontier function, efficiency scores derived under LML should be more reliable and less biased than efficiency ratings under nonparametric DEA and SFA alternatives.

One limitation of our analysis is the use of a single output instead of a multi-output technology (in which sorghum, wheat, soybean and corn output would be considered separately). However, Nauges et al. (2011) suggested that using multiple outputs can conduct to biased estimates due to the endogeneity problem. Our research can be extended in many different ways. Different methodological innovations to assess efficiency have been recently introduced in the literature. Noteworthy are the refinements regarding the measurement of technical efficiency in the presence of uncertainty through state-contingent techniques (Chambers and Quiggin, 2000). Failure to properly allow for risk can lead to biased efficiency estimates (O'Donnell et al., 2010). Extension of LML methods to a consideration dynamic issues constitutes another area that merits further attention. This is left for the near future research as a means to improve the specification of the frontier technology.

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Table 3.1. Summary statistics for the variables of interest

Variable	N=1258	
	Mean	Standard deviation
Total output (index)	154,193.14	164,521.51
Capital (index)	162,547.25	158,754.89
Land (acres)	1,277.89	1,103.34
Labor (AWU)	292.68	252.84
Chemicals inputs (index)	38,296.45	41,985.78
Other inputs (index)	24,398.16	25,388.22
Statistics on a per acre basis		
Total output (dollars/acre)	122.50	66.52
Capital (dollars/acre)	150.36	131.49
Labor (AWU/acre)	0.24	0.14
Chemicals inputs (dollars/acre)	29.11	16.98
Other inputs (dollars/acre)	19.48	12.68

Table 3.2. Summary statistics for the local estimates of σ_u^2 , σ_v^2 and λ

	σ_u^2	σ_v^2	λ
Maximum (100%)	1.14	0.26	22.20
Third quartile (75%)	0.03	0.10	0.59
Median (50%)	0.02	0.09	0.48
First quartile (25%)	1.93E-5	0.09	0.01
Minimum (0%)	6.93E-7	7.59E-4	0.30E-2

Table 3.3. Estimated LML production elasticities and observed input share for Kansas farms

Variable	Estimated elasticities	Observed input share
Land area	0.248 (0.070)	0.173 (0.129)
Labor	0.048 (0.066)	0.053 (0.084)
Capital	0.217 (0.050)	0.197 (0.118)
Chemical inputs	0.293 (0.047)	0.334 (0.132)
Other inputs	0.199 (0.041)	0.241(0.106)

Note: standard deviation in parenthesis

Table 3.4. Frequency distribution of technical efficiency scores

TE: Range (%)	Observations				(%)			
	LML[1]	DEA_{VRS}[2]	DEA_{CRS}[3]	SFA[4]	LML	DEA_{VRS}	DEA_{CRS}	SFA
<80	71	2	645	508	5.64	0.16	51.27	40.38
80-85	132	31	449	419	10.49	2.46	35.69	33.07
85-90	431	363	103	297	34.26	28.86	8.19	23.61
90-95	244	657	31	37	19.40	52.23	2.46	2.94
95-100	380	205	30	0	30.21	16.30	2.38	0
Mean	0.905	0.917	0.808	0.804				
Standard deviation	0.084	0.035	0.047	0.073				
Minimum	0.095	0.779	0.678	0.046				
Maximum	1.000	1.000	1.000	0.941				

[1]LML: local maximum likelihood. [2]VRS: variable returns to scale. [3]CRS: constant return to scale. [4]SFA: Stochastic Frontier Analysis.

Table 3.5. Kolmogorov-Smirnov test

Test	Value	p-value
LML vs. DEA VRS	0.264	0.000
LML vs. DEA CRS	0.713	0.000
LML vs. SFA	0.607	0.000

Table 3.6. Cluster analysis results

Farm TE		Cluster Low	Cluster Medium	Cluster High	Test of difference between means (significance
		0.78 (0.10)	0.88 (0.01)	0.96 (0.04)	
Farm size	Small <500 acres	64%	22.3%	12.7%	0.000**
	Medium (500- 1000 acres)	18.7%	24.8%	28.7%	
	Big >1000 acres	17.2%	52.9%	58.7%	
Irrigated land share (ratio)		0.05 (0.15)	0.09 (0.19)	0.09 (0.19)	0.007*
Rented land share (ratio)		0.49 (0.41)	0.62 (0.33)	0.57 (0.33)	0.000*
Unpaid labor share (ratio)		0.92 (0.23)	0.79 (0.29)	0.81 (0.29)	0.000*
Output (index)		55,404.96 (78,526.86)	160,623 (140,915.8)	181,890 (186,897.4)	0.000*
Yields (dollars/acre)		91.81 (54.18)	119 (47.14)	134.89 (77.29)	0.000*
Age (year)		63.28 (15.12)	56.88 (13.37)	58.23 (13.52)	0.000*
Education (dollars)		194.05 (1,203.36)	573.11 (2,462.07)	641.53 (3,109.10)	0.112
Subsidies (dollars)		10,450.91 (15,610.36)	24,986.47 (34,302.09)	27,443.01 (29,764.41)	0.000*
Non agricultural income (dollars)		17,535.24 (41,322.00)	11,938.25 (19,712.15)	9,653.33 (19,518.52)	0.000*
Number of observations		203	431	624	

Standard deviation in parenthesis. *,** indicate F-statistical and chi-square statistical significance at the 1%, respectively.

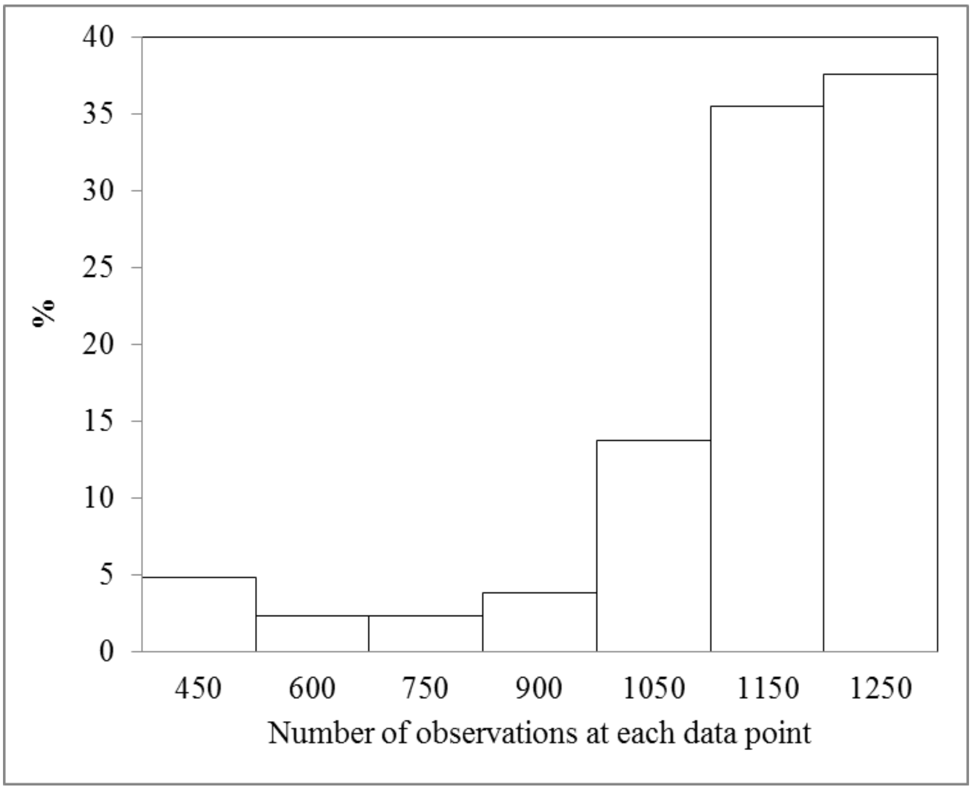

Figure 3.1. Distribution of the number of observations at each data point.

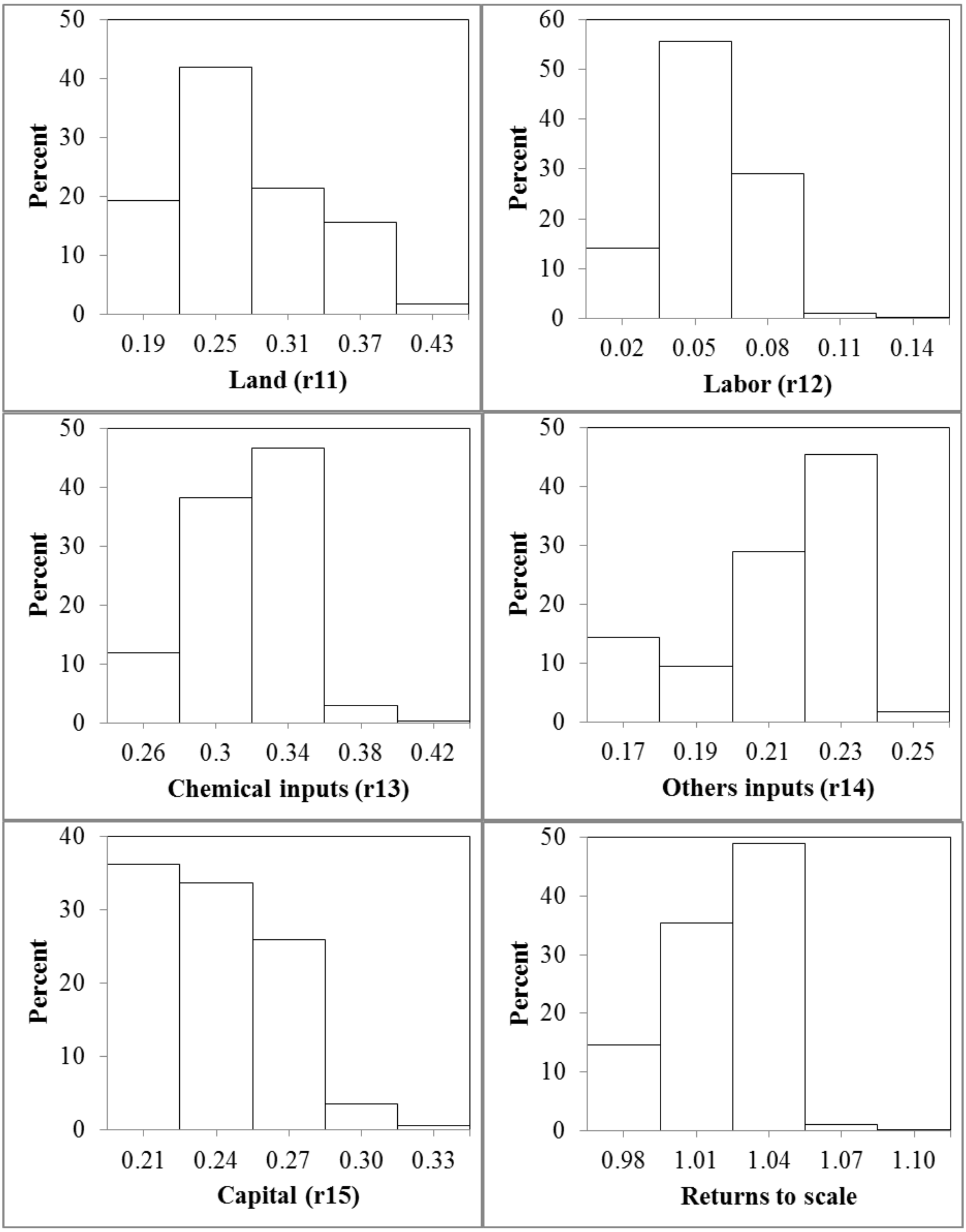

Figure 3.2. Distribution of localized estimates of input elasticities and returns to scale

Chapter 4

Technical and environmental efficiency of Catalan arable crop farms[13]

[13] Publication information: Guesmi, B., Serra, T., 2013. Technical and environmental efficiency of Catalan arable crop farms. *Applied Economic Perspectives & Policy journal (first-round review).*

4.1. Introduction

Intensive agricultural systems have several harmful impacts on humans, animals and the environment. This has increased social and political concerns regarding agriculture-related negative externalities. At the political level, these concerns have led European Union's (EU) agricultural policies to increasingly focus on environmental considerations. Interest in promoting agricultural practices that minimize pollution has been growing. Consistently, different policies have been devised to encourage farmers to use less chemical inputs and to adopt environmentally friendly practices. These alternative practices however, can affect the productivity and efficiency with which farms are operating, which in turn can influence their economic viability.

Since its inception, the EU's Common Agricultural Policy (CAP) has been continuously reshaping itself. While initial objectives focused on farm income support, policy scopes have been widened to embrace environmental preservation. Late CAP reform proposals made by the European Commission aim at aligning the CAP with the targets of the "Europe 2020 framework" and call for environmental sustainability, higher efficiency, effectiveness and equitability. Noteworthy among the reform proposals is the aim to redistribute CAP direct payments on the basis of both economic and environmental criteria. In light of current CAP reform debates, it is important to develop tools to support monitoring the impacts of policy and to assist in better targeting policy measures.

Derivation of farm-level technical and environmental efficiency (TE and EE, respectively) indices should be a relevant tool for improved CAP payment redistribution. While high TE measures are a pre-requisite for economic sustainability, high environmental performance indicators should contribute to environmental sustainability of agricultural practices. Recent literature on efficiency has been debating on the adequate methods to derive these measures.

Farm-level transition to environmentally sustainable practices can be regarded as a three-stage process involving different degrees of environmental impact reduction. The three stages are efficiency, substitution and redesign (Wossink and Denaux, 2007). Our analysis focuses on the first phase, which aims at minimizing the use of polluting inputs and optimizing input allocation to achieve the desired output levels. A farm can be considered as environmentally inefficient, if pollution per unit of input is above an ideal minimum. On the other hand, technical inefficiencies arise when firms are unable to maximize their output levels with minimum use of inputs (Farrell, 1957). While privately-run farms are likely to achieve a high level of TE regarding conventional input/output use, they are less likely to be environmentally efficient due to a lack of economic incentives and information, bounded rationality, or lack of external competitive pressure regarding environmental performance (Wossink and Denaux, 2007).

During the last decades, the scientific community has produced several research studies that attempt to evaluate the aggregate external costs of modern agriculture (Pimentel et al., 1992 and 1995; Evans, 1995 and 1996; Bailey et al., 1999; Tiezzi, 1999; Pretty et al., 2000; Le Goffe, 2000). Tegtmeier and Duffy (2004) place the value of the negative impact of agriculture on water, land, air and human health around 29.44 - 95.68 dollars per hectare in the USA. In another study, Pretty et al. (2000) obtained a greater value of 325[14] dollars for the United Kingdom, being the most relevant sources of environmental damage: contamination by pesticides, greenhouse gas emissions, damage to wildlife and habitats, as well as food poisoning by bacteria and viruses and other disease agents.

In contrast to most sustainability indicators that have been defined at an aggregate level, farm-level efficiency measures are directly linked to firm management decision making. While aggregate-level studies can be very useful for politicians and society at large, and can help designing suitable agricultural and environmental policies, they do not provide useful information for decision making units (DMU) who are more concerned about the economic and environmental performance of their holdings. Thus, unlike many environmental performance measures that have been defined at the aggregate level, our study focuses on estimating combined measures of TE and EE at the microeconomic level. To achieve this objective Coelli et al.'s (2007) efficiency measures are extended to a consideration of the stochastic environment in which production takes place.

The paper is organized as follows. In the next section, a literature review and the contribution of this work to previous literature is presented. Then, we describe the methodology used in our empirical analysis. The fourth section presents the data and results from the empirical implementation. We finish the paper with concluding remarks.

[14] Pretty et al. (2000) express this amount in GBP. The exchange rate used is 1GPB=1.56 US, which was obtained from http://www.measuringworth.com/.

4.2. Literature review

The first attempts to measure firm-level EE considered a firm's environmental impacts either as an input or an output. Färe et al. (1989), using Data Envelopment Analysis (DEA) techniques, incorporated pollution into productive efficiency analyses as a weakly disposable bad output, which implies the assumption that the reduction of pollution is expensive. The latter implies that, for a given technology, reducing pollution comes at the cost of reducing the amount of the good output. The authors developed a hyperbolic productive efficiency model that treats desirable and undesirable outputs asymmetrically, i.e., while producers get credit for providing desirable outputs, they are being penalized for generating undesirable outputs. This "enhanced" efficiency measure was compared with the conventional efficiency index where, by holding inputs fixed, one expands desirable outputs and ignores pollution. The comparison of these two efficiency measures shows the extent to which ignoring undesirable outputs distorts the magnitude of efficiency. Färe et al. (1996) decomposed the overall factor productivity for US fossil-fuel-fired electric utilities into an environmental index (under the weak disposability assumption for the undesirable outputs) and a productive efficiency index. They demonstrated that ignoring pollution leads to significant divergence in the rankings of the electric utilities. In another study, Färe et al. (2001) used Malmquist-Luenberger productivity index as a measure to weight the relative importance of bad outputs. They found that ignoring bad outputs leads to underestimate the annual productivity growth of US manufacturing sectors for the 1974-1986 period (on average, 1.7% vs. 3.6%).

Piot-Lepetit and Vermersch (1998) studied the TE and EE of a sample of French farms specialized in pig production. They considered pollution caused by organic nitrogen as an undesirable output. Using DEA techniques and assuming weak disposability of organic nitrogen, the authors found a limited ability to reduce nitrogen pollution for given output levels. Nitrogen surplus has also been treated as an environmentally detrimental input rather than as undesirable output (Reinhard et al., 1999). The authors provided separate estimates of output-oriented TE and input-oriented EE of Dutch dairy farms. They found that the latter achieve high levels of TE (0.89) and low levels of EE (0.44).

The work conducted by Arandia and Aldanondo (2007) constitutes an exception to published literature on TE and EE of Spanish farms. They focused on a sample of wine farms and studied their TE by means of a directional distance function that is fit to data by using DEA methods. Two bad outputs were considered: nitrogen and pesticide pollution. Under the strong disposability assumption, the average inefficiency was around 25%. If the weak disposability was imposed, inefficiency levels were reduced to 4%, the difference being caused by the opportunity costs of pollution reduction.

Another EE measure different from other approaches proposed in the literature was developed by Reinhard et al (2002). This methodology is based on two stages. While the first stage estimates both TE and EE using Stochastic Frontier Analysis (SFA), the second stage uses SFA to regress EE obtained from the first stage on explanatory variables that may explain EE. Conditional EE is then derived from the one sided error component of this second stage. Relatively low conditional environmental (0.57) and environmental (0.43) efficiency levels of Dutch dairy farms were found.

Asmild and Hougaard (2006) used a DEA model to estimate TE and EE of a sample of Danish pig farms. Unlike other studies that consider pollution as an undesirable output or input, Asmild and Hougaard (2006) disaggregated the nutrient surpluses into two flows: input and output. They suggested that, assuming variable returns to scale (VRS), EE levels are around 34-56%, which shows an important margin to improve the environmental performance of these farms.

While previous literature has paid considerable attention to adjusting efficiency and productivity measures by considering negative externalities associated to production, a few recent analyses have incorporated the provision of environmental goods in the vector of farms' good outputs (Omer et al., 2007; Areal et al., 2012). Areal et al. (2012) used SFA based on Bayesian procedure to assess TE of dairy farms in England and Wales and found efficiency scores and ranking according to these scores to change with incorporation of environmental outputs in the output vector. As a proxy for the provision of environmental goods, they used the share of permanent and rough grassland to total agricultural land area. Average efficiency scores changed from 0.91 to 0.83.

Førsund et al. (2008) and Murty et al. (2011) have shown that reduced-form technologies that consider pollution either as an input or as a weakly disposable output, have serious weaknesses. The materials balance principle, that represents the key role of inputs in residual generation, is proposed as an appropriate method to model pollution. Reinhard and Thijssen (2000) used the shadow cost approach to assess environmental performance of Dutch dairy farms, based on the materials balance condition. They found that mean technical and nitrogen efficiency are on the order of 0.84 and 0.56, respectively.

Based on materials balance principle, Coelli et al. (2007) suggested a new approach which, in contrast to previous research, does not require the introduction of an extra pollution variable in the production model. Coelli et al. (2007) illustrate their proposal by studying the environmental performance of a sample of farms specializing in pig-finishing in Belgium using DEA techniques under constant returns to scale (CRS) assumption. Results suggest that farms can produce their current output level with 15.7% fewer nutrient pollution. Thus, by improving farm's efficiency performance, and based on a cost reducing strategy, farmers avoid adopting expensive pollution abatement technologies.

While the production economics literature has heavily debated on the proper specification of technologies that involve both intended and unintended outputs such as pollution, less attention has been paid to the incorporation of the fundamentally stochastic nature of production into efficiency and productivity analyses. Productivity and efficiency analyses have often ignored the stochastic nature of production. Even the "stochastic frontier" model is typically grounded on the assumption that the underlying technology is non-stochastic. In industries such as agriculture where uncertainty is more the norm than the exception, this can lead to biased efficiency and productivity estimates, because effects due to uncertainty can either be attributed to productivity or efficiency differences. For example, a bad production outcome due to a stochastic factor beyond the control of farmers may be misconstrued as an inefficient production choice. An important challenge in production economics is thus to appropriately model the stochastic environment under which production takes place.

In line with mainstream efficiency analysis, Coelli et al. (2007) rely on the assumption that the underlying production technology is deterministic. The state-contingent approach proposed by Chambers and Quiggin (1998 and 2000) and built upon the theory developed by Debreu (1959), is based on the assumption that production under uncertainty can be represented by differentiating outputs according to the state of nature in which they are realized. This leads to a stochastic technology based on a state-contingent input correspondence. Under conventional representations of stochastic technologies, input-output relationships are studied conditional on the realized state of nature. Chambers and Quiggin (2000) have shown that while these representations are an extension of conventional non-stochastic representations of technology and can be easily empirically implemented, they impose relevant restrictions on the interaction between stochastic outputs and variable inputs. For example, non-substitutability between state-contingent outputs is imposed, i.e, it is assumed that producers can only respond to random shocks by modifying their input bundle, but not by re-allocating state-contingent outputs. This representation is known as the output-cubical technology (Chambers and Quiggin, 2000), and has been shown to potentially lead to important biases in efficiency estimates (O'Donnell et al., 2010).

Ex-ante measures of the random variables are required to overcome the output-cubicality assumption. Since historically, efforts have been focused on collecting ex-post production data, ex-ante measures are usually unavailable. Our work is innovative in that it relies on data collected by means of a survey that elicited information on ex-ante state-contingent outputs. When such measures are on hand, the methods used to study deterministic technologies can be easily applied to evaluate state-contingent technologies. By using the Arrow-Debrew-Savage framework, Chambers and Quiggin (2000) show that, in the presence of risk, the firm's cost and input demand functions depend on the outputs in all possible states of nature. Further, recognition that individuals with monotonic preferences minimize cost permits evaluation of production decisions independently on any specific assumption on risk attitudes.

Despite the relevance of state-contingent techniques, there are very few empirical applications based on this methodology. O'Donnell and Griffiths (2006) use Bayesian techniques to estimate a state-contingent production frontier. Chavas (2008) develops a state-contingent cost function and an econometric method to recover the ex-ante technology from the ex-post production data. Following Chavas (2008), Serra et al. (2010) apply state-contingent techniques to assess production decisions in US agriculture over the last century. Previous empirical approaches have not relied on survey-elicited ex-ante production data. This is a relevant contribution of this article to previous research.

4.3. Methodology

Recently, traditional measures of TE have been extended to integrate pollution considerations. Late developments within this literature have stressed the necessity to consider the materials balance condition in order to provide sound measures of farms' environmental performance. Coelli et al.'s (2007) proposal, based on this principle, is extended to allow for the stochastic conditions of production.

Consider a firm that uses a vector of $k = 1, 2, ..., K$ inputs, $\mathbf{x} \in \mathbb{R}_{+}^{K}$ to produce a state-contingent output, $\mathbf{y} = (y_1, ..., y_S)' \in \mathbb{R}_{+}^{S}$. The set of states of nature is represented by $\Omega = \{1, 2, ..., S\}$, and y_s represents the output realized under state of nature s. The feasible production set under the state-contingent approach, T, can be derived as follows:

$$T = \left\{ (\mathbf{y}, \mathbf{x}) \middle| \mathbf{x} \text{ can produce } \mathbf{y}; \mathbf{x} \in \mathbb{R}_+^K, \mathbf{y} \in \mathbb{R}_+^S \right\}, \tag{1}$$

where the production technology is defined to be convex, non-increasing in inputs, non-decreasing in outputs, and strongly disposable in inputs and outputs. Let $\mathbf{z} \in \mathbb{R}_+^S$ represent a surplus measure calculated using a materials balance equation, which is specified as a linear function of input and output vectors:

$$\mathbf{z} = \mathbf{a}'\mathbf{x}' - \mathbf{b}'\mathbf{y}', \tag{2}$$

where $\mathbf{a}$ and $\mathbf{b}$ represent vectors of known non-negative constants. The optimization problem seeks to determine the optimal combination of inputs for a given amount of output that minimizes the amount of the surplus (pollution caused in the production process).

Under the assumption that the output vector $\mathbf{y}$ is fixed or that the output vector is not capable of converting the polluting input into a usable form (i.e., $\mathbf{b}$ equals the zero vector), the first component of the surplus in equation (2) will be minimized when the aggregate pollutant content of inputs $(M = \mathbf{a}'\mathbf{x})$ is minimized. For a given vector of $k = 1, 2, ..., K$ pollution contents, $\mathbf{a} \in \mathbb{R}_+^K$, the minimum pollution associated with producing a specified amount of output, can be expressed as:

$$M(\mathbf{y}, \mathbf{a}) = \min_{\mathbf{x}} \left\{ \mathbf{a}'\mathbf{x} \middle| \langle \mathbf{y}, \mathbf{x} \rangle \in T \right\}, \tag{3}$$

Denote $\mathbf{x}_e$ the solution to the minimization problem in (3). $\mathbf{a}'\mathbf{x}_e$ and $\mathbf{a}'\mathbf{x}$ represent the minimum and the observed environmental damage, respectively. Following Farrell (1957), the technically efficient input vector $\mathbf{x}_t$ can be determined by solving the following optimization problem:

$$\mathrm{TE}(\mathbf{y}, \mathbf{x}) = \min_{\theta} \left\{ \theta \middle| \langle \theta\mathbf{x}, \mathbf{y} \rangle \in T \right\}, \tag{4}$$

where θ is a scalar that takes a value between zero and one. $\mathbf{x}_t$ is determined by $\mathbf{x}_t = \theta\mathbf{x}$ and the corresponding amount of pollution can be approximated by $\mathbf{a}'\mathbf{x}_t$.

Under the state-contingent approach to modeling risk, the production function is transformed from an ex-post to an ex-ante representation of technology (Chambers and Quiggin, 2000). Since ex-ante production is conditional upon the state of nature, each ex-post output quantity has a multivariate ex-ante representation ($\mathbf{y} = \left(y_1, \ldots, y_S\right)' \in \mathbb{R}_+^S$). The increase in the output vector size under the state-contingent approach may bring dimensionality issues that are specially relevant under SFA, as the number of parameters to be estimated grows substantially. Further, ex-ante state-contingent outputs tend to be strongly correlated with each other (Chavas, 2008), which is associated to potential multicollinearity issues in econometric model estimation. Overcoming multicollinearity problems in parametric approaches usually involves working with a reduced version of the actual state space. As is well known and in contrast to SFA, nonparametric DEA techniques neither rely on specific functional forms, nor on the covariance among input and output variables, which reduces the risk of misspecification issues that may lead to biased efficiency estimates. Gong and Sickles (1992) suggest that DEA techniques become more attractive as potential SFA misspecification issues grow. Following Färe et al. (1994), the DEA linear programming model to assess input-oriented TE levels can be expressed as:

$$\begin{aligned}
&\min_{\lambda,\theta} \theta \\
&\text{s.t.} \\
&-\mathbf{y}_i + \mathbf{Y}\lambda \geq 0 \\
&\theta \mathbf{x}_i - \mathbf{X}\lambda \geq 0 \\
&\mathrm{N1}'\lambda = 1 \\
&\lambda \geq 0
\end{aligned} \tag{5}$$

where N represents the number of farms. The constraint $N1'\lambda = 1$ is included to allow for VRS. Efficiency scores derived under VRS are compared with those obtained under CRS. The EE measure proposed by Coelli et al. (2007) is expressed as a ratio of minimum pollution over observed pollution:

$$\mathrm{EE} = \mathbf{a}'\mathbf{x}_e / \mathbf{a}'\mathbf{x} \tag{6}$$

where EE takes a value between zero and one, the latter indicating that the firm is fully environmentally efficient. The EE scores for observation i, using the DEA method (Coelli et al., 2007), are obtained from the following minimization problem:

$$\begin{aligned}
&\min_{\lambda,\mathbf{x}_i^e} \mathbf{a}_i'\mathbf{x}_i^e \\
&\text{s.t.} \\
&-\mathbf{y}_i + \mathbf{Y}\lambda \geq \mathbf{0} \\
&\mathbf{x}_i^e - \mathbf{X}\lambda \geq \mathbf{0} \\
&\mathbf{N1}'\lambda = 1 \\
&\lambda \geq \mathbf{0}
\end{aligned} \tag{7}$$

According to Coelli et al.'s (2007) model, environmental inefficiencies are caused both by technical inefficiencies that imply an excessive use of polluting inputs, and by allocative inefficiencies involving an inappropriate input mix given the observed $\mathbf{a}$ vector. Hence, EE is decomposed into two components: TE and environmental allocative efficiency (EAE):

$$\mathrm{TE} = \mathbf{a}'\mathbf{x}_t / \mathbf{a}'\mathbf{x} = \mathbf{a}'(\theta\mathbf{x}) / \mathbf{a}'\mathbf{x} = \theta\,, \tag{8}$$

and

$$\mathrm{EAE} = \mathbf{a}'\mathbf{x}_e / \mathbf{a}'\mathbf{x}_t\,, \tag{9}$$

Allocative efficiency is thus defined as the ratio of minimum pollution to the amount of pollution generated by the technically efficient input vector. All these efficiency measures (TE, EE, and EAE)[15] take a value ranging from zero to one and can be related through the following expression:

$$\mathrm{EE} = \mathrm{TE} \times \mathrm{EAE}\,. \tag{10}$$

Though a generalization of research results is difficult to make and data and methodologies used by different analyses are rather heterogeneous, damages derived from pesticide use are found to be one of the most relevant agriculture-related externalities. This

[15] See Coelli et al. (2007) for a graphical representation of the approach to measuring EE, TE and EAE.

study focuses on pollution derived from pesticide use. In line with Morse et al. (2006), Wossink and Denaux (2007) and de Koeijer et al. (2002), we build an index of pesticide contamination that accounts for the amount of pesticide applied and its toxicity. Through a farm-level survey, we collected detailed information on the quantities of active ingredients applied through herbicides, fungicides and insecticides. The total quantity of active ingredients, expressed in liters, was considered as a polluting input. As well known, different active ingredients have different environmental and health effects. To derive a single measure of pesticide pollution, we used a weighting procedure.

While different indices have been elaborated to measure the impacts of different active ingredients on the environment, animal and human health, they usually focus on a limited list of active ingredients. The Acceptable Daily Intake (α_i), obtained from the Footprint (2012) dataset, is the only index covering the full range of active ingredients used by our sample farms. α_i measures the quantity of active ingredients that can be daily ingested over a lifetime, without implying a significant health risk for humans.[16] This index is usually measured in mg per kilos of body weight per day (mg/kgbw/day). The vector of α_i's can be represented as:

$$\boldsymbol{\alpha} = (\alpha_1, \alpha_2, ..., \alpha_{\mathrm{n'}}), \tag{11}$$

the vector of weights applied to each active ingredient is expressed as:

$$\mathbf{a} = \left[a_1, a_2, ..., a_{n'}\right]. \tag{12}$$

where $a_i = \dfrac{\min(\boldsymbol{\alpha})}{\alpha_{\mathrm{i}}}$. The vector of weights was scaled so that their sum be equal to one. Pesticide, insecticide and herbicide pollution is approximated by: $\sum_{i=1}^{\mathrm{n}} a_i AI_i$, being AI_i the quantity of active ingredient *i* applied.

[16] While the use of Acceptable Daily Intakes offers a first approximation to toxicity, a more relevant measure of aggregate environmental impact should include the number of people affected by pollution.

4.4. Data and Results

4.4.1. Data

Our analysis uses cross sectional, farm-level data collected using a questionnaire that was distributed among 190 agricultural holdings specialized in the production of cereals, oilseeds and protein (COP) crops. The survey was conducted during the planting season in 2011 and includes detailed information on planned input use. We also obtained data on *ex-ante* outputs for three alternative states of nature: bad, normal and ideal growing conditions $y=(y_1, y_2, y_3)$.

Since farmers' responses regarding crop yield distribution are likely to be subjective, eliciting ex-ante output information is a complex process. Subjective opinions about what characterizes a bad, normal or ideal crop yield can lead to biased responses. To reduce subjectivity, one could provide farmers with detailed information on each crop-growing scenario (rainfall, temperature, frost, etc.). This, however, would increase survey complexity and cost, as a full characterization of crop-growing scenarios would require provision of a relevant amount of data during the interview. For example, providing the number of frost days during the growing season would render an incomplete picture if not accompanied by the distribution of these days over time. Incomplete scenarios would lead to highly inaccurate responses.

Final survey design was a trade-off between complexity and subjectivity, and was conditional upon feedback with technicians from Unió de Pagesos, which constitutes the largest farmer association in Catalonia. Unió de Pagesos was in charge of administering the survey. Highly qualified technicians from this institution recommended to obtain point estimates of yields under bad (y_1), normal (y_2) and ideal (y_3) growing conditions, without projecting specific scenarios. Yields under normal conditions usually represent average yields realized during a sufficiently long period of time. Once normal yields are identified, it is relatively easy for farmers to provide yields under bad and ideal conditions. Unió de Pagesos' technicians based their recommendation to obtain these point estimates on the argument that the more complex scenario-based alternative, would not provide substantially different results if designed correctly.

Chambers and Quiggin (2000) and Rasmussen (2003) defined state-allocable inputs as inputs that, ex-ante, can be allocated to different states of nature. To include these inputs in the production representation, the authors expanded the input vector to allow identifying the different impacts that inputs have on different states of nature. Budget restrictions, as well as the need to keep the survey short, precluded obtaining information on state-allocable inputs. This is left for further research as a means to improve the representation of the stochastic technology.

Output (y_s) represents farm COP production in Euros (€) under state $s = 1, 2, 3$. Inputs included in the analysis are: (X_1) total hectares (ha) of land planted to COP; (X_2) hired and family labor, expressed in hours; (X_3) capital input that aggregates the replacement value (in €) of machinery, other equipment and buildings used in the production process; (X_4) the expenditure in fertilizers expressed in €; (X_5) pesticide, herbicide and insecticide use (liters of active ingredients); (X_6) seed expenses, expressed in €; (X_7) energy input including fuels and lubricants, expressed in €; (X_8) contract work, expressed in €.

Table 4.1 provides summary statistics for the variables used in the analysis. Sample farms cultivate, on average, 75 hectares, a farm size above the national and the EU arable crop farms' average, of around 52 and 46 hectares, respectively (Farm Accountancy Data Network, FADN 2012). More than 95% of the COP area is devoted to wheat (36%) and barley (60%) production. Sample farms devote, on average, 552 hours to COP production during the growing season, of which more than 90% represents unpaid family labor.

Depending on crop growing conditions, farmers expect to obtain different output levels. While under bad conditions the average value of COP production is around 31 thousand € per farm, under ideal conditions average output is on the order of 70 thousand €. Under normal conditions, the value of COP production (51 thousand €) generated by our sample farms almost doubles the EU farms' average output (28 thousand €). Per ha statistics suggest our sample farms are more intensive than both national and EU farms: while EU and national farms have respectively, an average income of 627 and 428 € per ha, 670 € per ha is the average income of our sample farms under normal growing conditions.

Machinery and buildings used by sample farms amount to 134 thousand €, or 2,304 € per ha, above EU's average investment ratios on the order of 1,497 € per ha (FADN, 2012) and it is much higher than the national average (536 € per ha). While sample farms cultivate more land than EU arable crop farms, they spend less money in fertilizer than the latter (5,315 vs. 9,279 € annually). Total quantity of active ingredients used by our sample farms is, on average, on the order of 85 liters. Expenses in pesticides amount to 2,975€, below EU's average crop farms (5,120€). Annual expenses in seeds and energy are on the order of 3,866 and 4,913 €, respectively.

4.4.2. Empirical results

The DEA results are presented in table 4.2. Results show mean TE scores on the order of 0.93 and 0.87 under VRS and CRS, respectively, suggesting that our sample farms could use on average 7% (13%) fewer inputs to produce the same level of their current output. Returns to scale were studied to find that farms operate under increasing returns to scale. More than 70% of the observations have efficiency ratings greater than 0.90, showing relatively high performance levels. However, under CRS, only about one half of farms exhibit this performance. Under VRS (CRS) assumption, technical efficiencies range from a minimum of 0.57 (0.18) to a maximum of one, suggesting that our sample farmers present different skills to manage their holdings.

Our TE findings are consistent with previous studies looking at the performance of crop farms (Mathijs et al., 2001; Oude Lansink et al., 2002). Mathijs et al. (2001) compared the efficiency of family farms and partnerships with large-scale successor organizations of the collective and state farms (LSOs) using DEA methods. For crop farms and for the periods 1991-1992 and 1994-1995, they showed that, under CRS, partnerships display higher average TE (1.00 and 0.97, respectively) than do family farms (0.82 and 0.81) and LSOs (0.93 and 0.93) in 1991-1992 and 1994-1995, respectively. When VRS were assumed, partnerships and family farms were found fully technically efficient, while LSOs's TE was on the order of 0.97 in 1991-1992. However, in 1994-1995 LSOs became more efficient than family farms and partnerships (1.00, 0.98 and 0.97, respectively). In another study, Oude Lansink et al. (2002) used DEA to compare organic and conventional crop and livestock farms in Finland and found that organic crop producers have higher efficiency than conventional farms under CRS (VRS) : 0.91 (0.96) and 0.67 (0.72), respectively. In contrast, our results are far from the findings by Latruffe et al. (2005), who used DEA to assess the technical and scale efficiency of crop and livestock farms in Poland for two periods 1996 and 2000. They found scores under CRS (VRS) for crop farms on the order of 0.66 (0.70) and 0.57 (0.67) in 1996 and 2000, respectively.

Comparison with other studies that use different methodologies does not aim at recommending one particular methodology over another. Instead, we aim at checking the confidence and robustness of our findings, whether they concur or not with other results derived from different methods and whether they are or not within the range of existing estimates (Balcombe et al, 2006). Serra and Goodwin (2009) used a local maximum likelihood approach to assess technical efficiency of Spanish conventional and organic arable crop farms. Mean efficiency scores of 0.97 and 0.94 for conventional and organic crop farms were derived, respectively. These values are relatively close to our findings for VRS. In contrast, our findings are far from those found by Hadley (2006) and Zhu and Oude Lansink (2010). Hadley (2006) used SFA to estimate farm-level TE in England and Wales for the period 1982-2002 and found a mean TE of 0.75 for crop farms. Zhu and Oude Lansink (2010) used an output distance SFA function to analyze the impacts of CAP reforms on TE of crop farms in Netherlands, Germany and Sweden for the period 1995-2004. They found an average TE level of 0.64 in Germany, 0.76 in the Netherlands and 0.71 in Sweden.

The average EE scores are 0.74 (0.58) under VRS (CRS) assumption, indicating that farmers should be able to produce their current output with 26% (42%) fewer pesticide, herbicide and insecticide use. Results suggest that farmers who are environmentally efficient tend to be more technically efficient (high positive correlation of around 0.90 between the two measures has been found), supporting that an efficient use of chemical inputs improves both environmental and technical performance. As opposed to previous studies that found an adverse effect of environmental regulations on productivity (Färe et al., 2001), the high correlation between TE and EE for our sample farms implies complementarity between economic and environmental sustainability. Environmental efficiencies range from a minimum of 0.02 to a maximum of 1, suggesting important variability within sample farms.[17]

Environmental efficiency ratings imply that there is substantial scope to reduce chemical input use leaving current output levels unaltered. This reduction is likely to alleviate the negative environmental impacts of chemical inputs (contamination of surface and groundwater, loss biodiversity, etc…). If sample farms were environmentally efficient, around 26 % of current use of pesticides, insecticides and herbicides would be avoided (around 4,200 liters of active ingredients for our sample farms).[18] This reduction in pollution levels would take place at no cost and would not require the adoption of pollution abatement technologies. A more rational input use would suffice. Since environmental allocative inefficiency (EAE) is

[17] While previous analyses have modeled environmental efficiency, to our knowledge, none of them has focused on arable crop farms. Since comparing environmental efficiency across different types of farming (pig farming versus arable crop farming, for example) is not adequate, comparison with previous research results is not made here.

[18] Pesticide use savings would be above 40% under constant returns to scale assumption.

found to be the main source of environmental inefficiency, it looks like farmers are not using the correct input mix, given the observed level of riskiness associated to each active ingredient. Improvements in technical efficiency performance will also lead to higher environmental efficiency levels of our sample farms.

4.5. Concluding remarks

The productive efficiency literature has paid very little attention to environmental performance issues. Growing social and political concerns for the environmental impacts of agriculture make it necessary to study environmental and technical performance using robust methodologies that enable to derive reliable indicators. Recently, Coelli et al. (2007) proposed a new approach based on the materials balance concept that represents the relevant role of inputs in generating residuals.

This study contributes to the literature by extending Coelli et al.'s (2007) proposal to allow for the stochastic environment in which production takes place. The extension is based on the state-contingent methods (Chambers and Quiggin, 2000). The model is applied to derive combined technical and environmental efficiency levels achieved by 190 Catalan farms specialized in cereals, oilseeds and protein crop production. To our knowledge, this is the first empirical application that derives TE and EE measures using both the materials balance and state-contingent frameworks.

Our empirical findings suggest that our sample farms, on average, reach technical efficiency scores of 93% and thus that they can reduce input use by 7% while leaving output levels unaltered. The average environmental efficiency score, on the order of 74%, indicates ample scope to improve environmental performance and reduce pesticide use and pollution. These inefficiencies are, to a large extent, caused by allocative inefficiencies that involve an inappropriate input mix.

Some policy recommendations to increase the relatively low EE levels are as follows. First, since chemical input is partly applied out of habit (farmers tend to do what they have done in the past), information and training courses on how to adequately apply chemical inputs may improve the agricultural sector's environmental performance. Second, CAP subsidy redistribution on the basis of environmental criteria, may act as an effective tool to motivate farmers to adopt environmentally friendly practices. Finally, since environmental inefficiencies are mainly due to allocative issues, providing farmers with better information on the environmental impacts of different pesticides, herbicides and insecticides, should improve environmental performance. Besides economic incentives penalizing the use of those chemicals with stronger harmful effects, encouraging farmers to produce environmental goods should further ensure better environmental efficiency levels.

One limitation of this analysis is that budget restrictions, as well as the need to keep the survey short, precluded obtaining information on state-allocable inputs, as well as on possible sources of inefficiency. This is left for future research as a means to improve the representation of the stochastic technology.

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Table 4.1. Summary statistics for the variables used in the analysis

Variable		Mean	Standard deviation
Output (€)	(y_1)[1]	30,576.97	33,155.16
	(y_2)[2]	50,958.65	51,672.67
	(y_3)[3]	70,431.86	74,793.60
Land (ha)	(X_1)	74.81	72.68
Labor (hours)	(X_2)	552.10	656.46
Capital (€)	(X_3)	133,721.63	126,557.95
Fertilizers (€)	(X_4)	5,314.76	7,352.18
Pesticides (liters of active ingredients)	(X_5)	85.34	117.19
Seeds (€)	(X_6)	3,866.07	3,750.11
Energy (€)	(X_7)	4,912.87	5,334.41
Contract work (€)	(X_8)	2,916.54	4,018.97
Statistics on a per hectare basis			
Output (€/ha)	(y_1)	391.31	131.76
	(y_2)	669.85	144.29
	(y_3)	912.83	214.04
Capital (€/ha)		2,303.74	2,785.71
Labor (hours/ha)		6.88	4.86
Fertilizers (€/ha)		71.75	63.61
Pesticides (liters of active ingredients /ha)		1.04	0.72
Seeds (€/ha)		52.46	16.98
Energy (€/ha)		66.97	43.68
Contract work (€/ha)		63.17	68.42

[1] y_1 : bad growing conditions. [2] y_2 : normal growing conditions. [3] y_3 : ideal growing conditions.

Table 4. 2. Summary statistics for DEA results

Efficiency measures	TE		EE		EAE	
	VRS	CRS	VRS	CRS	VRS	CRS
Mean	0.93	0.87	0.74	0.58	0.76	0.61
Standard deviation	0.11	0.16	0.37	0.41	0.35	0.40
Minimum	0.57	0.18	0.02	0.00	0.04	0.00
Maximum	1.00	1.00	1.00	1.00	1.00	1.00

Table 4.3. Frequency distribution of DEA efficiency scores

Efficiency scores:	**VRS**			**CRS**		
Range (%)	**TE**	**EE**	**EAE**	**TE**	**EE**	**EAE**
<60	2	63	57	17	96	88
60-70	9	2	5	14	4	8
70-80	19	3	3	23	3	4
80-90	25	4	6	34	3	4
90-100	134	117	118	101	83	85
Mean	0.93	0.87	0.74	0.58	0.76	0.61
Standard deviation	0.11	0.16	0.37	0.41	0.35	0.40
Minimum	0.57	0.18	0.02	0.00	0.04	0.00
Maximum	1.00	1.00	1.00	1.00	1.00	1.00

Chapter 5

Conclusions

Farm-level productivity and efficiency analyses have important implications both for firm management decisions and policy design. By targeting firms not previously investigated and using new methodological approaches, this thesis contributes to the literature both from a methodological and an empirical point of view. The thesis is integrated by three independent research articles. The first article's scientific contribution is mainly of an empirical nature, as it targets organic farms in Spain that have received little attention by the efficiency and productivity literature. More specifically, it focuses on assessing productivity and technical efficiency differences between organic and conventional grape farms in Catalonia, as well as the factors that affect technical efficiency levels. The second article, with a strong methodological orientation, uses recent innovative techniques to study technical efficiency of Kansas farms specialized in arable crop production. Finally, the third research paper extends recent proposals to derive combined environmental and technical efficiency measures, and applies them to study performance of Catalan arable crop agricultural holdings.

In spite of the significant recent growth in organic farming in Spain, the literature on the performance of Spanish organic farming is still insignificant. The first research paper contributes to fill this gap. The methodological approach adopted in the first paper consists of a stochastic frontier model in which inefficiency effects are assumed to be a function of firm-specific characteristics. Our research is pioneer in that it measures the contribution of farmers' preferences regarding environmental preservation and economic performance to efficiency. The analysis is based upon a sample of 141 organic and conventional Catalan farms that specialize in grape growing.

Our empirical findings suggest that organic farmers, on average, display higher technical efficiency scores than their conventional counterparts (80% and 64%, respectively). However, organic farms show lower productivity than conventional ones. Our results identify adoption of organic practices, experience, family labor share in total labor, farm location and farmer environmental preferences as the variables that are more relevant in explaining technical inefficiencies. Holding more experience and/or using organic practices leads to higher efficiency levels. Conversely, farms that rely on a higher proportion of unpaid labor, are located in a less favored area, or whose manager has strong environmental preservation preferences, tend to be less efficient.

In the second research article, local maximum likelihood methods, recently proposed by Kumbhakar et al. (2007), are used to assess Kansas farms efficiency levels. The analysis is based on farm-level data obtained from farm account records from the Kansas Farm Management Association dataset covering the period 2000-2010. In spite of the interesting features of local estimation methods, its use has been limited to a few empirical studies due to implementation complexities.

Empirical results support the relevance of using the LML approach through the variation in the localized parameter estimates representing the variance of the composite error term and input elasticities. Results show that Kansas farms reach 91 % of their maximum potential output indicating that farmers could increase their output by 9% without the need to increase input use and without changing current technology. Technical efficiency scores derived from the LML approach [0.905] are higher than those of the DEA model under CRS [0.808] and SFA [0.804] and close to DEA-VRS [0.917] ratings. According to the KS test, the efficiency score distributions obtained from DEA and SFA differ from LML distribution ratings. Since LML allow for both stochastic error terms, as well as for flexibility in the functional form representing the frontier function, LML efficiency scores may be more reliable and less biased than those derived under nonparametric DEA and SFA alternatives.

In the third research paper, we use the recent Coelli et al.'s (2007) method based on the materials balance concept to assess both technical and environmental efficiencies. We expand this method to allow for the stochastic environment in which production takes place. The extension is based on the state-contingent methods proposed by Chambers and Quiggin (1998 and 2000). To our knowledge, no previous published work has studied environmental efficiency using state-contingent methods. This constitutes our major contribution to the literature. On the other hand, to date, no studies have previously focused on the assessment of technical and environmental efficiency of Spanish agriculture using this methodology.

The analysis is based on farm-level data collected using a questionnaire distributed among 190 Catalan arable crop agricultural holdings. Our empirical findings suggest that sample farms present high average technical efficiency scores of 93%, indicating that they can reduce input use by 7% while leaving output levels unaltered. The average environmental efficiency score, on the order of 74%, indicates ample scope to improve environmental performance and reduce pesticide use and pollution by 26%. These inefficiencies are, to a large extent, caused by allocative inefficiencies.

As well known and also shown in this thesis, efficiency estimates are very sensitive to the method used to estimate the frontier (parametric or non-parametric), to the functional form representing the production frontier and the distribution of the error term. The use of improved techniques is thus key for meaningful efficiency analyses. This thesis implements different methodologies in the analysis of farm performance, from well-known methods to very innovative approaches, providing credible case studies in applying different approaches and providing evidence for their value.

Improving technical efficiency allows for a reduction in production costs and increases competitiveness. This is specially useful to agricultural sectors where consumers are generally unwilling to pay higher prices and the marketing power of middlemen and retailers becomes more and more relevant. Firm management and policy implications are proposed along the thesis that are based on the obtained results. According to these, promotion of extension services that transfer knowledge to farmers is expected to improve production performance through added education and experience. Enhanced efficiency levels may also be pursued through more professionalized management of agricultural holdings by using more specialized labor force. Information and training courses on how to adequately apply chemical inputs could enhance the agricultural sector's environmental performance. Similar results might be achieved by redistributing CAP subsidies on the basis of environmental criteria, or by promoting economic incentives that penalize the use of harmful chemicals. Providing better information on the environmental impacts of different pesticides, herbicides and insecticides and how to adequately use them may also lead to improved environmental performance.

Several shortcomings affecting our analysis as well as proposals for future research can be pointed out. One limitation is the small number of organic farms used in the first research paper. Collecting additional farm-level organic farming data would increase the reliability and the number of farms represented by our results. The curse of dimensionality affecting local maximum likelihood techniques used in the second article makes it difficult to use more sophisticated representations of production technology. Further, panel data techniques are not taken into account when estimating the model. Developing local maximum likelihood methods applicable to panel data techniques is another pending research issue. Different methodological innovations to assess efficiency have been recently introduced in the literature that could be applied to our data. Noteworthy are the innovations regarding dynamic efficiency measurement that do not rely on the assumption of firm's ability to adjust instantaneously and that allow for the dynamic linkages of production decisions (Tsionas, 2006; Silva and Stefanou, 2007; Rungsuriyawiboon and Stefanou, 2007; Serra et al., 2010; Emvalomatis et al., 2011;Serra et al., 2011). Extension of local maximum likelihood methods to a consideration dynamic issues constitutes another area that merits further attention. In the third article, budget restrictions, as well as the need to keep the survey short, precluded obtaining information on state-allocable inputs, as well as on possible sources of inefficiency.

This is left for future research as a means to improve the representation of the stochastic technology. Allowing for the impacts of other pollution sources such as fertilizers, will allow deriving more reliable environmental performance estimates.

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