The influence of public subsidies on farm technical efficiency: A robust conditional nonparametric approach

European Journal of Operational Research 259 (2017) 1112–1120

Contents lists available at ScienceDirect

European Journal of Operational Research

journal homepage: www.elsevier.com/locate/ejor

Innovative Applications of O.R.

The influence of public subsidies on farm technical efficiency: A robust conditional nonparametric approach

Jean Joseph Minviel [a,*], Kristof De Witte [b,c]

[a] SMART, INRA, 35000, Rennes, France
[b] Top Institute for Evidence Based Education Research, Maastricht University, 6200 MD Maastricht, the Netherlands
[c] Leuven Economics of Education Research, Faculty of Economics and Business, KU Leuven, Leuven 3000, Belgium

ARTICLE INFO

Article history:
Received 24 May 2016
Accepted 7 November 2016
Available online 12 November 2016

Keywords:
Data Envelopment Analysis
Conditional efficiency
Nonparametric econometrics
Public subsidies
Farms

ABSTRACT

The objective of this paper is to assess the influence of public subsidies on farm technical efficiency using recent advances in nonparametric efficiency analysis. To this end, we use robust conditional frontier techniques as well as insights from recent developments in nonparametric econometrics. The paper contributes to the ongoing methodological discussion on how to model the effect of public subsidies on farmers' production decisions. The analysis is conducted using an unbalanced panel data of 1604 observations from 313 French farms located in the French region Meuse over the period 2006–2011. The estimates indicate that public subsidies influence negatively the conditional technical efficiency of farms. This suggests that public subsidies affect both the range of the attainable set for the inputs and outputs and the distribution of the efficiency scores inside the attainable set.

1. Introduction

In most developed countries, public subsidies constitute the main agricultural policy instrument and represent a large part of farmers' income. For instance, the yearly budget of the European Union (EU) Common Agricultural Policy (CAP) is about 50 billion euros, of which subsidization absorbs 70%, on average (European Commission, 2014a). In addition, about one-half of the net value added of farms (FNVA) in the EU countries is due to public subsidies (European Commission, 2014b). Theoretical studies predict that such subsidies may influence farmers' behavior (Ciaian & Swinnen, 2009; Hennessy, 1998; Just & Kropp, 2013). In this context, an extensive literature investigates the extent to which public subsidies influence farmer's production decisions. This paper contributes to this literature by focusing on technical efficiency which can be seen as an indicator of the optimal use of production factors. The subsidy-efficiency nexus is a crucial research question for agricultural policymakers, since it might provide information on the influence of public subsidies and the optimal use of agricultural production factors. The objective of the current paper is to assess the subsidy-efficiency nexus in a fully nonparametric framework, such that specification errors are minimized.

The empirical modeling of the subsidy-efficiency nexus remains a challenging issue. The main complexity lies in the absence of clear conceptual guidance on how to model public subsidies. As a result, there exists a plethora of empirical models in which the influence of public subsidies on technical efficiency is often treated in an ad hoc way (McCloud & Kumbhakar, 2008), and this may lead to misleading empirical results in terms of the direction of the effect (see Minviel & Latruffe, 2016, for a meta-analysis).

In the subsidy-efficiency literature, the most commonly used empirical frameworks include the parametric Stochastic Frontier Approach (SFA) and the nonparametric two-stage Data Envelopment Analysis (DEA). In the SFA framework the relationship between public subsidies and technical efficiency is estimated by specifying a likelihood function which accounts for the dependence of the inefficiency component on subsidies (see Battese & Coelli, 1995). In the two-stage DEA approach, efficiency scores are estimated in the first stage and then these scores are regressed on subsidies in the second stage.

This literature presents two main deficiencies. First, the two-stage DEA approach relies on a separability condition which states that the input-output set is not influenced by contextual factors (Simar & Wilson, 2011). This assumption is likely to be very restrictive regarding public subsidies, since it is theoretically demonstrated that public subsidies may influence the input-output space (see Ciaian & Swinnen, 2009; Hennessy, 1998; Serra, Zilberman, Goodwin, & Featherstone, 2006). Second, likely to account for this theoretical fact, a number of papers, using SFA or DEA, model

* Corresponding author. Fax: +33 2 23 48 53 80.
E-mail addresses: Jean-Joseph.Minviel@rennes.inra.fr, j.jminviel@yahoo.fr (J.J. Minviel), k.dewitte@maastrichtuniversity.nl, Kristof.dewitte@kuleuven.be (K. De Witte).

http://dx.doi.org/10.1016/j.ejor.2016.11.014
0377-2217/

subsidies as input or as output (see Hadley, 2006; Kroupová & Malý, 2010; Malá, Červena, & Antouškova, 2010; Mamardashvili, Emvalomatis, & Jan, 2016; Rasmussen, 2010; Silva & Marote, 2013; Silva, Arzubi, & Berbel, 2004; Trnková, Malá, & Vasilenko, 2012). However, treating subsidies as input or as output may create a modeling artifact. On the one hand, when subsidies are modeled as output they artificially inflate output production and tend to erroneously provide positive subsidy-efficiency nexus (Minviel & Latruffe, 2016). In addition, a theoretical (economic) argument against the modeling of subsidies as output is that subsidies are not an output generated by the classic agricultural production technology (Minviel & Latruffe, 2016). On the other hand, subsidies should not be modeled as input since they are generally used to purchase parts of conventional inputs included in the efficiency model (see Ciaian & Swinnen, 2009; Latruffe, Davidova, Douarin, & Gorton, 2010). Thus, modeling subsidies as input results in double counting. In this respect, the conditional efficiency framework (Cazals, Florens, & Simar, 2002; Daraio & Simar, 2005, 2007; De Witte & Kortelainen, 2013), which allows explicitly accounting for the influence of subsidy on farmers' production decisions without treating them as input or as output, seems to be suitable for examining the subsidy-efficiency nexus. In addition, it relaxes the separability assumption of the two-stage DEA approach (see Daraio & Simar, 2007, for more details), which may be unrealistic in the case of the subsidy-efficiency nexus.

This paper contributes to the literature by providing, to our best knowledge, the first application of the conditional efficiency methodology to examine the subsidy-efficiency nexus. More precisely, the paper contributes to the ongoing methodological discussion on how to model the effect of public subsidies on farmers' production decisions in production efficiency analysis. To do so, the paper tests the theoretical assumption that public subsidies may influence the input-output space in a production efficiency framework. In other words, the main question addressed in the paper is whether economic conditions created by public subsidies affect both the range of the attainable set for the inputs and outputs and the distribution of the efficiency scores inside the attainable set. A second methodological contribution of the paper concerns the use of the wild bootstrap procedure which ensures consistent estimates in case of heteroskedasticity (see, Henderson & Parmeter, 2015). Third, the paper relies in the estimation on a variability function which allows investigating the influence of public subsidies on the variance of the efficiency scores, and hence the risk effect of public subsidies in a non-parametric framework.

Our estimations show that public subsidies influence negatively farm technical efficiency. At first glance, this result is consistent with previous findings on the subsidy-efficiency nexus in the non-parametric efficiency literature. Nevertheless, in previous studies this negative effect concerned only the distribution of inefficiencies inside the best practice frontier. In contrast, as we use a conditional efficiency framework, our results highlight that public subsidies affect both the range of attainable values for the inputs and outputs, and thus the shape of the boundary of the attainable set, and the distribution of the efficiency scores inside the attainable set. Regarding the variability function, the estimates indicate that public subsidies influence positively the variance of the efficiency scores. For the output-oriented technical efficiency, this suggests that an increase in public subsidies may induce a higher variance in output. This result is in line with the fact that public subsidies may alter farmers' risk attitude (Serra, Zilberman & Gil, 2008), which may result in a reduction of technical efficiency.

The remainder of the paper is structured as follows. In Section 2 we describe the methodological framework. Section 3 presents the data. In Section 4 we discuss the empirical results. Concluding remarks follow in Section 5.

2. Methodology

We use a conditional efficiency model which explicitly assumes that subsidies may influence the choice and the level of input use. This fully nonparametric framework has been introduced by Cazals et al. (2002) and Daraio and Simar (2005, 2007).

Within this framework, a production process which combines inputs $X \in \mathbb{R}^p_+$ to produce outputs $Y \in \mathbb{R}^q_+$ given contextual variables $Z \in \mathbb{R}^r_+$ (including subsidies) can be fully characterized by the following joint conditional probability (Cazals et al., 2002; Daraio & Simar, 2007):

$$\begin{aligned} H_{X,Y|Z}(x, y|Z = z) &= Prob(X \le x, Y \ge y|Z = z) \\ &= Prob(Y \ge y|X \le x, Z = z)Prob(X \le x|Z = z) \\ &= \mathcal{S}_{Y|X,Z}(y|x, z)F_{X|Z}(x|z), \end{aligned} \tag{1}$$

where $\mathcal{S}_{Y|X,Z}(y|x, z)$ denotes the conditional survival function of Y, i.e., $\mathcal{S}_Y(y) = Prob(Y \ge y)$, and $F_{X|Z}(x|z)$ the marginal conditional distribution function of X, i.e., $F_X(x) = Prob(X \le x)$. Expression (1) gives the probability for a unit operating at level (x, y) to be dominated, i.e., that another unit may produce as much output using no more input, given $Z = z$. The support of this probability is defined by the production technology ψ^Z. An output-oriented conditional efficiency score is defined by the upper boundary of the support of $\mathcal{S}_{Y|X,Z}(y|x, z)$ as follows:

$$\theta(x, y|z) = sup\left\{\theta \,\middle|\, \mathcal{S}_{Y|X,Z}(\theta y, |x, z) > 0\right\} = sup\left\{\theta \,\middle|\, H_{X,Y|Z}(x, \theta y|\, z) > 0\right\}. \tag{2}$$

The robust order-m specification for expression (2) can be obtained by the conditional output-oriented order-m frontier which defines the expected maximum level of outputs achievable for a subset of m production units randomly drawn with replacement by a conditional q-variate survival function $\mathcal{S}_{Y|X,Z}(\theta y|x, z)$. Thanks to the randomization, the order-m frontier does not necessarily envelop extreme values. In this sense, it is robust to outliers and atypical values in the data (Bonaccorsi, Daraio, & Simar, 2006). Also, for any value y, there exists $\tilde{\theta}^z_m(x, y) = sup\{\theta|(x, \theta y) \in \tilde{\psi}^z_m(x)\}$ such that the conditional output-oriented order-m efficiency measure is defined as:

$$\begin{aligned} \theta_m(x, y|z) &= E_{Y|X,Z}\left(\tilde{\theta}^z_m(x, y)|X \le x, Z = z\right) \\ &= \int_0^\infty \left[1 - \left(1 - \mathcal{S}_{Y|X,Z}(uy|x, z)\right)^m\right] du. \end{aligned} \tag{3}$$

For multivariate z including continuous and categorical drivers, the empirical counterpart of the survivor function $\mathcal{S}_{Y|X,Z}(y|x, z)$ can be estimated using the mixed-multivariate kernel function as follows:

$$\hat{\mathcal{S}}_{Y|X,Z,n}(y|x, z) = \frac{\sum_{i=1}^n I(X_i \le x, Y_i \ge y)K_{\hat{h}}(z, z_i)}{\sum_{i=1}^n I(X_i \le x)K_{\hat{h}}(z, z_i)}, \tag{4}$$

where $K_{\hat{h}}(.) = h^{-1}K((z, z_i)h^{-1})$ is a r-variate[1] product kernel function (see, De Witte & Kortelainen, 2013, for more details), $\hat{h} = (\hat{h}_1, \ldots, \hat{h}_r)$ a vector of r estimated bandwidth parameters, and $I(.)$ is an indicator function which equals to unity if its argument is true and zero otherwise. Thus, the conditional efficiency estimator $\hat{\theta}_m(x, y|z)$ is given by plugging $\hat{\mathcal{S}}_{Y|X,Z,n}(y|x, z)$ into Eq. (3).

The survival function is estimated as a locally weighted mean. In this sense, the kernel function controls the weights, while the bandwidths control the size of the neighborhood. For the current study, we apply the Epanechnikov kernel for continuous variables and the Aitchison and Aitken kernel for categorical variables (see Li & Racine, 2007; Racine, 2008, for more details). Notice that the kernel choice has little influence on the accuracy of

[1] $K_{\hat{h}}(.)$ is multivariate in the sense that it defines $Z \in \mathbb{R}^r$ univariate kernels.

the estimates (Ahamada & Flachaire, 2008; Silverman, 1986), but the choice of the bandwidths is of crucial importance since the bandwidths can cause undersmoothing or spurious oversmoothing[2] (Daraio & Simar, 2007; Racine & Li, 2004). In addition, in the context of conditional efficiency measurement, the choice of the bandwidths has to account for the influence of the exogenous drivers on the production decisions to avoid the separability assumption (Bădin, Daraio, & Simar, 2010). Thus, we follow Bădin et al. (2010) to choose the optimal bandwidths, using the least squares cross-validation (LSCV) approach which consists in minimizing the weighted integrated squared error (ISE). The LSCV approach provides consistent bandwidth estimates in cases of large sample, as in the case of the current study (Henderson & Millimet, 2005), and outperforms the nearest-neighbor method proposed by Daraio and Simar (2007) and Bădin et al. (2010).

To estimate the influence of public subsidies on technical efficiency, we use the location-scale nonparametric regression model suggested by Bădin, Daraio, and Simar (2012):

$$\theta_i(x_i, y_i|z_i) \ = g(z_i) + \sigma(z_i)\xi_i, \tag{5}$$

where ξ_i is an error term with $E(\xi_i)=0$ and $V(\xi_i)=1$. In this setup, $g(.)=E[\theta_i(x_i, y_i|z_i)\,]$ and $\sigma^2(z_i)=V[\theta_i(x_i, y_i|z_i)\,]$. Hence, on the one hand, the location-scale model allows capturing the marginal effects of z on technical efficiency by analyzing the behavior of $E[\theta_i(x_i, y_i|z_i)\,]$ as a function of z. On the other hand, it enables exploring the effects of z on the dispersion of the efficiency scores by analyzing the behavior of $V[\theta_i(x_i, y_i|z_i)\,]$ as a function of z. g(.) and $\sigma^2(.)$ can be estimated in a two-step procedure (Bădin et al., 2012), using kernel local linear regression methods. In the first step, the local linear estimator of g(.) is given by the following minimization setting:

$$\underset{\{\alpha,\beta\}}{\operatorname{argmin}} \sum_{i=1}^{n} \left[\theta_i(x_i, y_i|z_i) - \alpha - \beta\left(z_i^c - z^c\right)\right]^2 K_h(z, z_i), \tag{6}$$

where K_h is the generalized product kernel function defined in (4), h denotes the bandwidth matrix, $\alpha(z^d, z^c)$ denotes the intercept and $\beta(z^c)$ are the local linear gradients, $z^c \in \mathbb{R}^r$ is a vector of continuous contextual drivers, and $z^d \in \mathbb{R}^v$ stands for a vector of discrete contextual drivers. Note that in (6), continuous regressors z^c are treated in a local linear way, while discrete regressors z^d are treated in a local constant one. In the second step, the local linear estimator of $\sigma^2(.)$ is obtained by regressing the squares of the residuals of the first step on z using the same minimization setting as in (6). The kernel local linear regression is used since it allows avoiding edge bias (Su, Chen, & Ullah, 2009).

As suggested by Bădin et al. (2012), the residuals (ξ_i) of the Eq. (5) can be used for the purposes of managerial efficiency analysis. For a given unit (x, y, z), the residuals can be expressed as follows:

$$\xi_i = \frac{\theta_i(x_i, y_i|z_i) - g(z_i)}{\sigma(z_i)} \tag{7}$$

Expression (7) can be seen as the unexplained part of the conditional efficiency. In our application this corresponds to the remaining part of the conditional efficiency after removing the location and the scale effects due to Z. In this sense, if Z is independent of ξ_i, Bădin et al. (2012) called ξ_i managerial efficiency since it depends only on the managers' ability and not on the environmental factors. Large values for ξ_i indicate poor managerial performance, while small or negative values indicate good managerial performance.

[2] For irrelevant variables the bandwidths converge to infinity (oversmoothing).

3. Data description

The data consist of an unbalanced panel of 1604 observations from 313 French farms located in the French region Meuse over the period 2006–2011. The data concern farmers who are voluntary enrolled in a regional accounting office so as to be guided in the management of their farms. Our dataset includes information on farm production structure, on farm financial results, and on agricultural subsidies. For the estimations, we use one aggregated output, four classical inputs, and some contextual factors. The selection of these variables is in line with earlier literature (e.g., Bakucs, Latruffe, Ferto, & Fogarasi, 2010; Bojnec & Latruffe, 2009; Kumbhakar, Lien, & Hardaker, 2014; Zhu, Karagiannis, & Oude Lansink, 2011). The aggregated output is measured as the value of the total production in euros including crop output and livestock output. The four classical inputs include the utilized agricultural area (UAA) in hectares, the labor used in annual working units (AWU) which are full-time yearly equivalents, the value of intermediate consumption in euros, and the value of the farm capital in Euros.

Notice that we employ a stock variable for farm capital. This measure of capital inputs is sometimes questioned since it does not account for the fact that capital is an input that is not consumed, but rather provides a flow of capital services. To account for this, the stock variable should be replaced by a flow that represents the service provided by the stock. However, the estimation of the flow requires data about physical depreciation, obsolescence, replacement, and durability which are not available in our dataset. In addition, as indicated in Yotopoulos (1967), the flow of capital services in a year could be approximated by the annual expenses of fixed capital, which are given by the rental price of capital assets per unit of time, times the unit worked in a year. Unfortunately, such data are also unavailable in our dataset. Hence, as usual in applied studies (e.g., Baležentis & De Witte, 2015; Bojnec & Latruffe, 2013; Kumbhakar, Tsionas, & Sipiläinen, 2009), we use a stock variable for farm capital, but we acknowledge that this variable may lead to an underestimation of the efficiency scores.

Monetary values for inputs and outputs are widely used in efficiency analysis due to their availability. However, one should keep in mind that efficiency scores estimated using monetary values reflect a mixture of technical and allocative efficiency. The use of monetary values may lead to significant artificial difference when comparing efficiency scores over time. For instance, artificial changes may occur in the evolution of the input-output combinations and thus in the evolution of efficiency scores given price effects. To attenuate price effects and eliminate mechanical increase in prices, it is important to deflate monetary values. Even though deflation allows uncovering the real evolution in monetary values, it does not necessarily convert them to real physical quantities. However, as mentioned in Sipiläinen and Oude Lansink (2005) and Zhu et al. (2011), this procedure assumes that farmers face the same prices and allows recovering implicit physical quantities for inputs and outputs variables measured in value.

The contextual factors include the total subsidy received by farmers on a per hectare basis; a dummy variable equal to one for individual farms, and zero otherwise (i.e. partnerships or companies). The contextual drivers also include a time trend variable for capturing time variant effects. In the period covered by the current study, coupled direct payments and decoupled direct payments to farmers represent the main forms of agricultural subsidies in the European Union (EU) Common Agricultural Policy (CAP). Hence, the total subsidy considered in this paper concerns mainly coupled and decoupled payments received by farmers. Coupled payments are subsidies linked to the production of a particular crop or a particular type of livestock, while decoupled payments are subsidies which are given to farmers without production requirements. In this study we consider the total subsidy received by farmers

Table 1
Summary statistics for the main variables used.

	Mean	St. dev.	Min	Max
Output				
Total production (Euros)	231,614	140,578	34,513	1,197,557
Inputs				
UAA (hectares)	207.97	102.76	61.63	689.88
Labor (AWU)	2.31	1.11	0.5	8
Intermediate consumption (Euros)	206,045	115,447	53,623	1,081,641
Capital (Euros)	294,822	178,450	14,242	1,274,381
Contextual variables				
Individual farm (dummy)	0.18	0.39	0	1
Subsidy per hectare (Euros)	225.74	75.92	100.22	463.82
Number of observations		1604		

Table 2
Empirical estimates for the conditional efficiency model.

Regressor	*Marginal effects*		*Dispersion effects*	
	Bandwidths	*Estimates*	*Bandwidths*	*Estimates*
Subsidy per hectare	43.41	−4.2E−05 *** (4.75E−06)	81.98	2.80E−05*** (4.86E−06)
Individual farm	0.31	3.87E−04** (1.8E−04)	0.07	2.8 E−04 (2.2E−04)
Time trend	0.13	−1.6E−02 *** (7.4E−04)	0.61	−2.64E−04*** (1.34E−10)
Mean conditional efficiency			0.89	
Mean unconditional efficiency			0.87	
Number of observations			1604	

Note: (1) *** indicates significance at 1% levels. (2) Bootstrapped standard error in brackets.

since our dataset does not distinguish between the different types of subsidy for the period considered. Nevertheless, in the period covered by the present study the major part of the subsidies received by farmers is in the form of decoupled payments (see also Rizov, Pokrivcak, & Ciaian, 2013). The indicator variable for individual farms enables us to investigate the efficiency discrepancy between individual and company farms (see Bakucs, Latruffe, Ferto, & Fogarasi, 2010; Gorton & Davidova, 2004). More precisely, this variable allows investigating the influence of governance structure on farm performance.

Based on the previous discussion on the deflation, all monetary values are expressed in 2006 constant Euros using the appropriate deflators obtained from the French National Institute of Statistics and Economic Studies (INSEE) (agricultural output price index, intermediate agricultural input price index, capital price index, and consumer price index). Summary statistics for the main variables used are presented in Table 1. This table indicates that the average utilized agricultural area (UAA) is roughly 208 ha, and farms produce an average of 231,614 Euros in annual value of final product. The total labor used amounts, on average, to 2.31AWU (1 AWU corresponds to 2200 work hours). Intermediate consumption and capital used equals roughly 206,000 Euros and 295,000 Euros, respectively. Subsidy payments average 225 Euros per ha, and this value ranges for the sample from a low of 100 Euros per ha to a high of 464 Euros per ha. There are only 18% of individual farms in the sample.

4. Empirical results

Estimation results concerning the mean effects obtained from the conditional efficiency model are reported in Table 2. The standard errors reported in Table 2 are computed using the wild bootstrap procedure. The wild bootstrap procedure ensures consistent estimates in case of heteroskedasticity (see, Henderson & Parmeter, 2015, for more details). The size of the partial frontier m is chosen from Fig. 1.

Fig. 1 graphically illustrates how to estimate the size of the partial frontiers of order m. In this picture, $f(m)$ is the curve of the percentage of super-efficient observations in the spirit of the order-m frontier (Cazals et al., 2002). The figure shows the percentage of super-efficient observations in the vertical axis and the sizes of the partial frontiers m in the horizontal axis. Daraio and Simar (2007) argue that the size of the partial frontier m should be chosen as the value of m from which the percentage of super-efficient observations decreases smoothly with m. Accordingly, with reference to Fig. 1, we set the size of the order-m frontier to 500. This implies that a farm is compared to 500 randomly drawn observations consuming at most the same amounts of inputs.

The mean conditional technical efficiency amounts to 0.89, suggesting that farmers achieve on average 89 percent of the maximum potential output in their production. This may also be understood in the sense that, in our sample, farmers could increase their output by 11 percent without increasing their input use. In other words, they could improve their technical efficiency level by 11 percent. As it can be seen from Table 2, the mean unconditional efficiency score is slightly lower than the conditional counterpart and it amounts to 0.87.

The first columns of the estimates from Table 2 present the bandwidths. None of the estimated bandwidths converge to infinity. This suggests that all regressors are relevant for explaining farm technical efficiency (Daraio & Simar, 2007; Racine & Li, 2004). In this light, Table 2 shows that public subsidies influence negatively farm technical efficiency. More precisely, the estimated parameter for public subsidies indicates that an increase of 100 euros per hectare in subsidies leads to a 0.4 percent decrease in farms' technical efficiency. At first glance, this inverse nexus is consistent with previous findings on the subsidy-efficiency nexus in the non-parametric efficiency literature (e.g., Bojnec & Latruffe, 2013; Ferjani, 2008; Nastis et al., 2012; Skevas, Oude Lansink, & Stefanou, 2012). The standard theoretical explanation for the inverse relationship lies in the wealth (or income) effect of public subsidies (see Hennessy, 1998). Indeed, the extra income brought by subsidization may distort farmers' incentive to work efficiently as they may decide to substitute subsidy income with farm (or market) income (Skevas et al., 2012). It must be noticed that the mean conditional efficiency score is higher than the mean unconditional one, while public subsidies appear to be detrimental to technical efficiency. This may be due to the fact that we do a multivariate analysis and hence the conditional efficiency scores do not depend only on subsidies (see Bădin et al., 2012; Serra & Oude Lansink, 2014; and Baležentis & De Witte, 2015, for comparison purposes).

Fig. 2 gives a full picture on the marginal effect of subsidies on farm technical efficiency. This contrasts to Table 2 which presents only the mean effects. The upper and the lower dashed lines are 95 percent confidence interval. The figure shows the efficiency scores in the vertical axis and the amount of subsidy per hectare in the horizontal axis. It confirms that the overall effect of public subsidies on technical efficiency is negative. More precisely, Fig. 2 shows that the technical efficiency scores decrease with an increase in the amount of subsidy per hectare received by farmers.

As explained in Bădin et al. (2012), the conditional efficiency measures depend not only on the boundary, they also depend on the distribution of the efficiency scores inside the boundary. As such the significant effect of subsidies on the conditional efficiency measures suggests that subsidies influence the position of the boundary and the distribution of the efficiency scores inside the boundary. In this sense, our results signal that the separability assumption between the input-output space and subsidies seems unrealistic for our sample of French farms. However to go a step further in our analysis, we use the ratio of conditional over unconditional efficiency scores, first for the full frontier and then for the median frontier (order α-frontier ratio, with $\alpha = 0.5$) to dis-

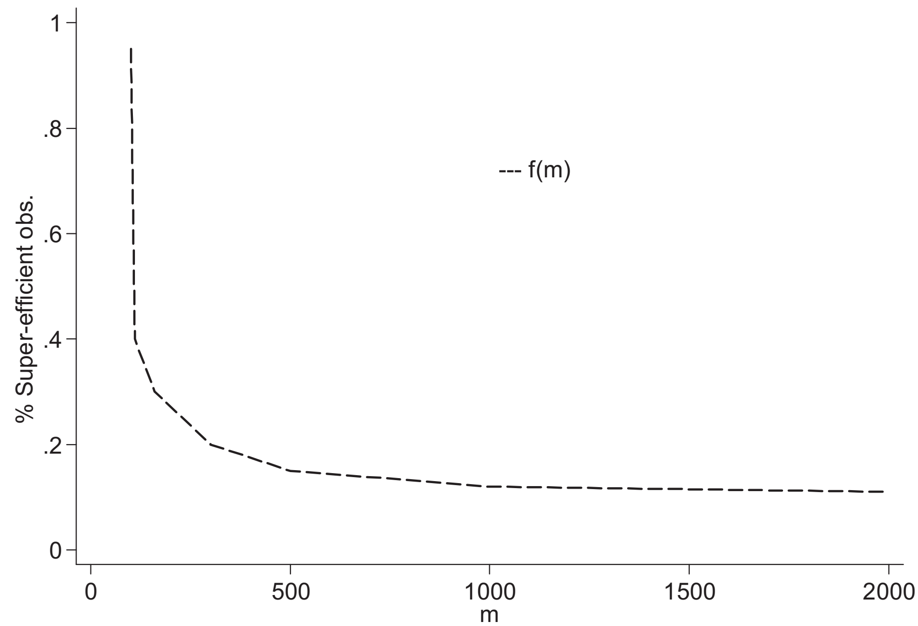

Fig. 1. Estimation of the size of the partial frontier m.
Note: Following Daraio and Simar (2007), the size of the partial frontier m is chosen as the value of m from which the percentage of super-efficient observations decreases smoothly with m.

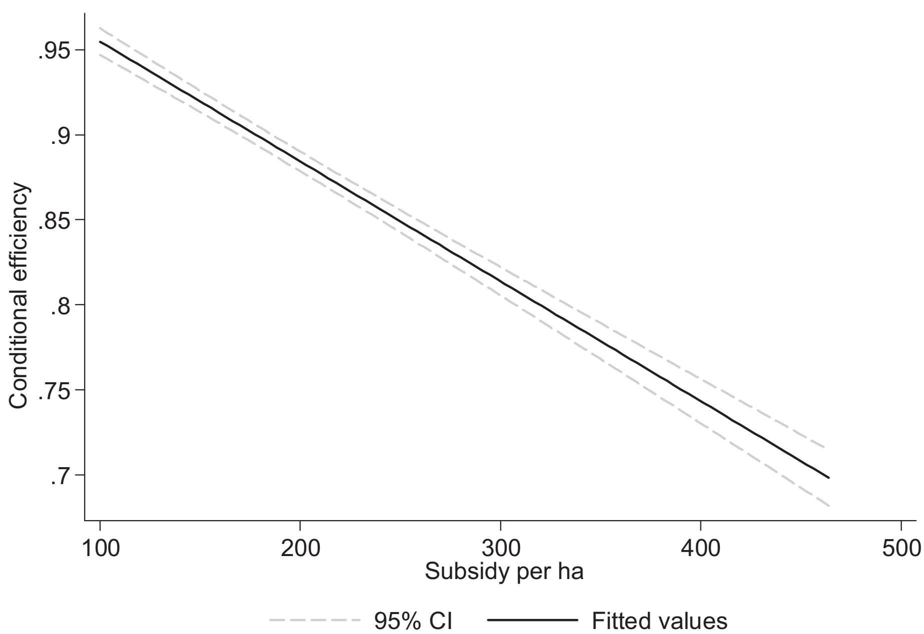

Fig. 2. Marginal effects of subsidies on the farms' conditional efficiency scores.

entangle the effects of subsidies on the shift of the frontier and their effects on the distribution of the efficiency scores. The results regarding the effects of subsidies (our main variable of interest) on the full frontier ratio are illustrated in Fig. 3, while their effects on the partial frontier ratio are presented in Fig. 4.

The main message from Fig. 3 is that the conditional efficiency frontier moves down the unconditional one when public subsidies are increasing. For the median frontier, Fig. 4 indicates that the probability of being near from the frontier (being more efficient) is decreasing for larger values of subsidies. As such, Figs. 3 and 4 roughly confirm that public subsidies affect both the range of the attainable set for the inputs and outputs and the distribution of the efficiency scores inside the attainable set (see Simar & Wilson, 2015). In order words, our result highlights that public subsidies affect the production process by influencing the production possibilities and the input-output combinations. This indicates that the separability condition (which assumes that external factors do not influence the boundary of the production set) does not hold in our data, suggesting that the traditional two-stage approach would be flawed (or meaningless) for our sample of French farms (see Bădin, Daraio, & Simar, 2014; Mastromarco & Simar, 2015). These results are very interesting since they show that with the conditional efficiency framework, we can examine the influence of public subsidies on the input-output space without treating them as input or as output (see Minviel & Latruffe, 2016). In addition, our results are in line with studies that theoretically demonstrated that public subsidies may influence the input-output space (see Ciaian & Swinnen, 2009; Hennessy, 1998; Serra et al., 2006).

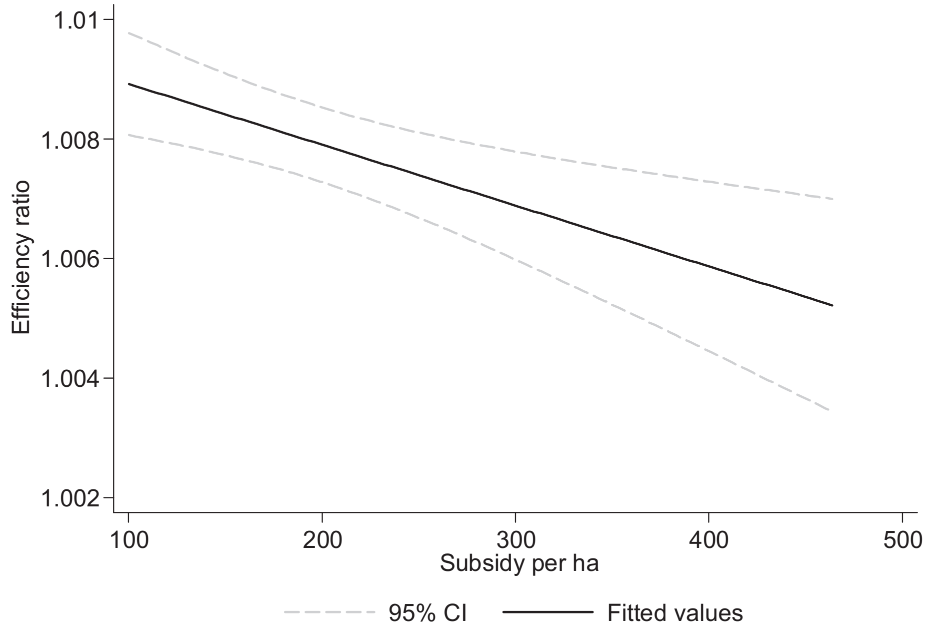

Fig. 3. Marginal effects of subsidies on the ratio conditional-unconditional efficiency for the full frontier.

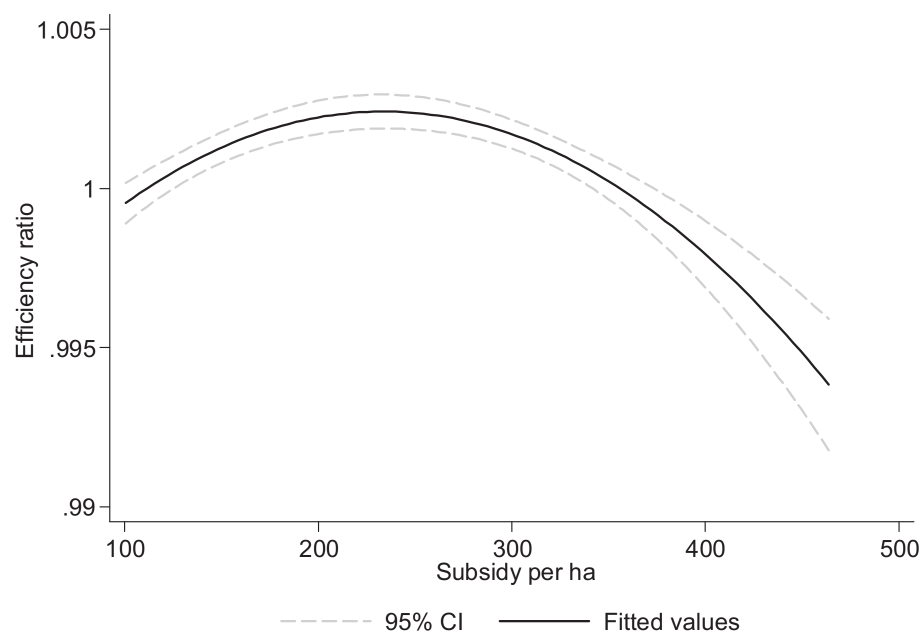

Fig. 4. Marginal effects of subsidies on the ratio conditional-unconditional efficiency for the median frontier (the middle of the distribution of the efficiencies).

Another important implication of the conditional efficiency framework is that it is in line with a fundamental aspect of the well established stochastic frontier model (SFA). In fact, in the SFA framework, as in the conditional efficiency framework, the efficiency scores are estimated by accounting for the influence of the contextual variables (see Battese & Coelli, 1995; Kumbhakar, Ghosh, & McGuckin, 1991; Zhu & Oude Lansink, 2010). In our case, this allows translating the effect of subsidies on technical efficiency into change in output production as in Zhu et al. (2011). In this line, the negative effect of subsidies on the conditional efficiency scores implies that mixed payments including coupled subsidies and more decoupled subsidies (the subsidy variable used in the current study) tend to reduce farm production. This may be due to the fact that, as a source of non-stochastic income, such subsidies generate a wealth effect and an insurance effect which result in decreasing farmers' incentive to produce (see Hennessy, 1998; Kumbhakar et al., 2014; Sipiläinen, Kumbhakar, & Lien, 2014; Zhu et al., 2011).

The estimates presented in Table 2 also display that individual farms are more efficient than partnership or company ones. As indicated in Table 2, the coefficient on *individual farm* implies that individual governance of farm causes 0.04 percent increase in technical efficiency. Although no clear cut conclusion can be found in the literature on the effect of individual firms on performance (see Bakucs et al., 2010; Gorton & Davidova, 2004), one possible explanation for this positive effect can be drawn from the Principal-Agent theory (Gorton & Davidova, 2004; Mathijs & Vranken, 2000). Indeed, regarding the motivation of workers, the lack of self-enforcing incentive structure in company farms may lead to Principal-Agent problems. That is, the lack of self-enforcing

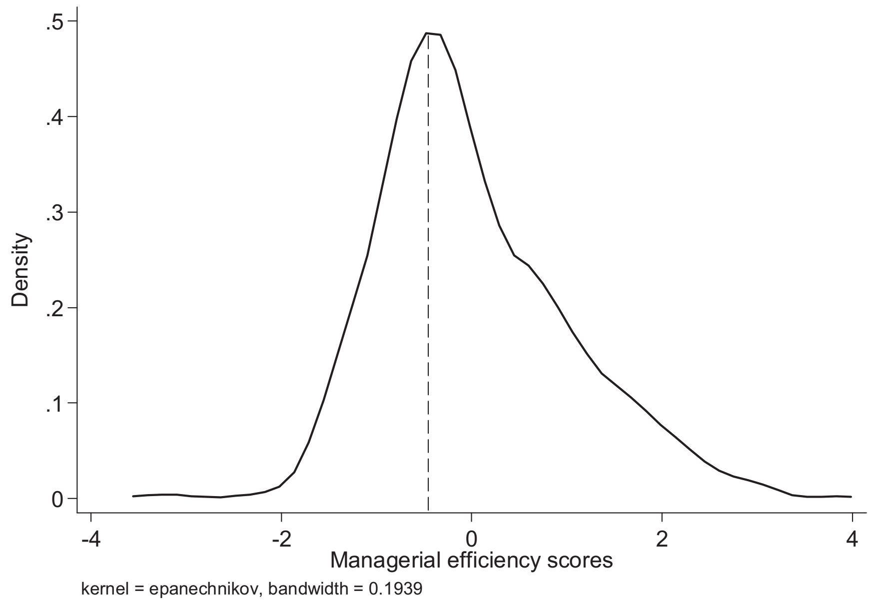

Fig. 5. Nonparametric kernel distribution of the estimated managerial efficiency scores.

incentive may induce high costs for monitoring and controlling workers effort and thus reduces technical efficiency of company farms (Gorton & Davidova, 2004; Mathijs & Vranken, 2000). As for the trend variable, we find that technical efficiency decreases over time. Regarding the variability function, the estimates indicate that public subsidies influence positively the dispersion of the efficiency distribution. For the output oriented technical efficiency, this suggests that an increase in public subsidies may induce a higher variance in output. This result confirms the fact that public subsidies may alter farmers' risk attitude (Serra et al., 2008).

Fig. 5 illustrates the distribution of the estimated idiosyncratic residuals ($\hat{\xi}_i$) for our sample of French farms. Recall that these residuals ($\hat{\xi}_i$) are obtained by whitening the conditional efficiency scores from the effects of the environmental factors. Importantly, for our sample, the linkages between $\hat{\xi}_i$ and the environmental factors are very low. Indeed, the correlation between $\hat{\xi}_i$ and subsidies is 0.0008 and the correlation ratios between $\hat{\xi}_i$ and the two qualitative variables (time and individual farm) are 0.009 and 0.01, respectively. These low correlations suggest that the values of $\hat{\xi}_i$ can be safely interpreted as managerial efficiency scores. Large values for $\hat{\xi}_i$ indicate poor managerial performance, while small or negative values indicate good managerial performance (Bădin et al., 2012). In this line, it must be remarked from Fig. 5 that the distribution of the estimated idiosyncratic residuals (the managerial efficiency scores) shows a peak below zero. This indicates good managerial performance for our sample of French farms (Bădin et al., 2012; Daraio, Bonaccorsi, & Simar, 2015).

5. Concluding remarks

This paper contributes to the literature by suggesting an empirical model that explicitly accounts for the theoretical fact that public subsidies may influence the choice and the level of input use, and thus output level. In particular, we suggest the use of the conditional efficiency model for analyzing the subsidy-efficiency nexus. The advantages of this framework are twofold. First, it relaxes the "separability assumption" of the traditional two-stage DEA approach, which is unrealistic in many practical cases such as the case of the subsidy-efficiency nexus. Second, it allows accounting for the influence of public subsidies on the input-output space without treating them as input or as output. In this respect, the paper contributes to the ongoing methodological discussion on how to model the effect of public subsidies on farmers' production decisions regarding the efficiency literature. Other contributions of the paper include (i) the use of the wild bootstrap procedure which ensures consistent estimates in case of heteroskedasticity, and (ii) the estimation of a variability function which allows investigating the risk effect of public subsidies, in a non-parametric efficiency framework.

Our estimates show that public subsidies influence negatively the conditional technical efficiency of farms. At first glance, this result is consistent with previous findings on the subsidy-efficiency nexus in the nonparametric efficiency literature. Nevertheless, our results are quite different from the previous findings in the sense that they concern both the effects of subsidies on the boundary of the attainable production set and the distribution of the efficiency scores inside the attainable set. This contrasts to earlier studies that are based on a "separability condition" which states that subsidies do not influence the boundary of the production set, but only the distribution of inefficiencies inside the best practice frontier. Our results clearly show that the separability condition does not hold in our data, suggesting that the traditional two-stage approach would be flawed (or is even meaningless) for our sample of French farms. In other words, in contrast to the previous studies, the conditional efficiency framework highlights that public subsidies affect both the production possibilities and the probability of being near or far from the efficient frontier. This suggests that governmental policies that provide financial support (public subsidies) to farmers may alter the efficient choice and use of production factors. As such, this may help policy-makers in defining subsidization policy to guide the efficient use of inputs having environmental and social impacts (such as chemical fertilizers, chemical pesticides, and labor).

However, as in previous studies, the aggregated efficiency approach used in this paper dictates that public subsidies may distort optimal use of all the inputs used by farmers. To consistently investigate this issue, further research could focus on multidirectional conditional efficiency analyses (MEA) as in Baležentis and De Witte (2015). The conditional MEA framework (Baležentis & De Witte, 2015) allows investigating input specific efficiencies from aggregated efficiency scores, and at the same time accounting for the influence of contextual drivers on these scores. Consequently, the conditional MEA framework may provide more information to policy makers with respect to the efficient use of a given input.

On the other hand, the negative effect of subsidies on the conditional efficiency scores suggests that public subsidies tend to reduce farm production. Recall that the subsidy variable considered in this paper concerns mainly decoupled and coupled payments. These mixed payments aim at supporting farmers' income and preserving strategic farming systems. Our results show that the mixed payments have a side effect of decreasing farmers' competitiveness by decreasing their technical efficiency and their production. This raises the question of whether there is a more effective way to support farms. In this line, further research could focus on new approaches for subsidy allocation as in Amores and Contreras (2009) and on multicriteria analysis for better resource management (Hayashi, 2000). It is also recommended that further research uses advanced modeling approaches which allow a simultaneous contraction of inputs and bad outputs, and expansion of good outputs including environmental outputs (Dakpo, Jeanneaux, & Latruffe, 2016; Daraio & Simar, 2014; Färe, Margaritis, Rouse, & Roshdi, 2016; Halkos and Tzeremes, 2013; Latruffe and Desjeux, 2016; Tzeremes, 2015), for a full picture on the effects of subsidies on production decisions.

Acknowledgements

The authors would like to thank participants of the 13th International Conference on Data Envelopment Analysis, Technische Universität, Braunschweig, Germany, 24-27 August 2015, for their valuable comments on the previous versions of this paper. The comments and suggestions by the Editor (Robert Graham Dyson, PhD) and the three anonymous re-viewers are also greatly appreciated.

References

Ahamada, I., & Flachaire, E. (2008). *Econométrie non-paramétrique*. Paris: Economica.
Amores, A. F., & Contreras, I. (2009). New approach for the assignment of new European agricultural subsidies using scores from data envelopment analysis: Application to olive-growing farms in Andalusia (Spain). *European Journal of Operational Research, 193*(3), 718–729.
Bădin, L., Daraio, C., & Simar, L. (2010). Optimal bandwidth selection for conditional efficiency measures: A data-driven approach. *European Journal of Operational Research, 201*(1), 640–663.
Bădin, L., Daraio, C., & Simar, L. (2012). How to measure the impact of environmental factors in a nonparametric production model. *European Journal of Operational Research, 223*, 818–833.
Bădin, L., Daraio, C., & Simar, L. (2014). Explaining inefficiency in nonparametric production models: The state of the art. *Annals of Operational Research, 214*, 5–30.
Bakucs, L., Latruffe, L., Ferto, I., & Fogarasi, J. (2010). The impact of EU accession on farms' technical efficiency in Hungary. *Post-Communist Economies, 22*(2), 165–175.
Baležentis, T., & De Witte, K. (2015). One- and multi-directional conditional efficiency measurement – Efficiency in Lithuanian family farms. *European Journal of Operational Research, 245*(2), 612–622.
Battese, G., & Coelli, T. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics, 20*, 325–332.
Bojnec, S., & Latruffe, L. (2009). Determinants of technical efficiency of Slovenian farms. *Post Communist Economies, 21*(1), 117–124.
Bojnec, S., & Latruffe, L. (2013). Farm size, agricultural subsidies and farm performance in Slovenia. *Land Use Policy, 32*, 207–217.
Bonaccorsi, A., Daraio, C., & Simar, L. (2006). Advanced indicators of productivity of universities. An application of robust nonparametric methods to Italian data. *Scientometrics, 66*(2), 389–410.
Cazals, C., Florens, J.-P., & Simar, L. (2002). Nonparametric frontier estimation: A robust approach. *Journal of Econometrics, 106*, 1–25.
Ciaian, P., & Swinnen, J. F. (2009). Credit market imperfections and the distribution of policy rents. *American Journal of Agricultural Economics, 91*(4), 1124–1139.
Dakpo, K. H., Jeanneaux, Ph., & Latruffe, L. (2016). Modelling pollution-generating technologies in performance benchmarking: Recent developments, limits and future prospects in the nonparametric framework. *European Journal of Operational Research, 250*(2), 347–359.
Daraio, C., Bonaccorsi, A., & Simar, L. (2015). Rankings and university performance: A conditional multidimensional approach. *European Journal of Operational Research, 244*, 918–930.
Daraio, C., & Simar, L. (2005). Introducing environmental variables in nonparametric frontier models: A probabilistic approach. *Journal of Productivity Analysis, 24*(1), 93–121.
Daraio, C., & Simar, L. (2007). Advanced robust and nonparametric methods in efficiency analysis. *Methodology and applications*. New York: Springer.
Daraio, C., & Simar, L. (2014). Directional distances and their robust versions: Computational and testing issues. *European Journal of Operational Research, 237*, 358–369.
De Witte, K., & Kortelainen, M. (2013). What explains the performance of students in a heterogeneous environment? Conditional efficiency estimation with continuous and discrete environmental variables. *Applied Economics, 45*(17), 2404–2412.
European Commission (2014a). 7th Financial report from the commission to the European parliament and the council. Commission staff working document.
European Commission (2014b). EU farm economics overview, based on FADN data 2011. European Commission staff working document.
Färe, R., Margaritis, D., Rouse, P., & Roshdi, I. (2016). Estimating the hyperbolic distance function: A directional distance function approach. *European Journal of Operational Research, 254*, 312–319.
Ferjani, A. (2008). The relationship between direct payments and efficiency in Swiss farms. *Agricultural Economics Review, 9*(1), 93–102.
Gorton, M., & Davidova, S. (2004). Farm productivity and efficiency in the CEE applicant countries: A synthesis of results. *Agricultural economics, 30*, 1–16.
Hadley, D. (2006). Patterns in technical efficiency and technical change at the farm-level in England and Wales, 1982–2005. *Journal of Agricultural Economics, 57*, 81–100.
Halkos, G., & Tzeremes, N. G. (2013). A conditional directional distance function approach for measuring regional environmental efficiency: Evidence from the UK regions. *European Journal of Operational Research, 227*(1), 182–189.
Hayashi, K. (2000). Multicriteria analysis for agricultural resource management: A critical survey and future perspectives. *European Journal of Operational Research, 122*(2), 486–500.
Henderson, D. J., & Millimet, D. L. (2005). Environmental regulation and US state-level production. *Economics Letters, 87*, 47–53.
Henderson, D. J., & Parmeter, C. F. (2015). *Applied Nonparametric Econometrics*. New York: Cambridge University Press.
Hennessy, D. A. (1998). The production effects of agricultural income support policies under uncertainty. *American Journal of Agricultural Economics, 80*(1), 46–57.
Just, D. R., & Kropp, J. D. (2013). Production incentives from static decoupling: Land use exclusion restrictions. *American Journal of Agricultural Economics, 95*(5), 1049–1067.
Kroupová, Z., & Malý, M. (2010). Analysis of agriculture subsidy policy tools: Application of production function. *Politiká Ekonomie, 6*, 774–794.
Kumbhakar, S. C., Ghosh, S., & McGuckin, J. T. (1991). A generalized production frontier approach for estimating determinants of inefficiency in US dairy farms. *Journal of Business and Economic Statistics, 9*(3), 279–286.
Kumbhakar, S. C., Lien, G., & Hardaker, J. B. (2014). Technical efficiency in competing panel data models: A study of Norwegian grain farming. *Journal of Productivity Analysis, 41*, 321–337.
Kumbhakar, S. C., Tsionas, E. G., & Sipiläinen, T. (2009). Joint estimation of technology choice and technical efficiency: An application to organic and conventional dairy farming. *Journal of Productivity Analysis, 31*, 151–161.
Latruffe, L., Davidova, S., Douarin, E., & Gorton, M. (2010). Farm expansion in Lithuania after accession to the EU: The role of cap payments in alleviating potential credit constraints. *Europe-Asia Studies, 62*(2), 351–365.
Latruffe, L., & Desjeux, Y. (2016). Common Agricultural Policy support, technical efficiency and productivity change in French agriculture. *Review of Agricultural, Food and Environmental Studies, 97*, 15–28.
Li, Q., & Racine, J. (2007). *Nonparametric econometrics: Theory and practice*. Princeton: Princeton University Press.
Malá, Z., Červena, G., & Antouškova, M. (2010). Analysis of the impact of Common Agricultural Policy on plant production in the Czech Republic. *Acta Universitatis Agriculturae et Silviculturae Mendelianae Brunensis, 59*(7), 237–244.
Mamardashvili, Ph., Emvalomatis, G., & Jan, P. (2016). Environmental performance and shadow value of polluting on Swiss dairy farms. *Journal of Agricultural and Resource Economics, 41*(2), 225–246.
Mastromarco, L., & Simar, L. (2015). Effect of FDI and time on catching up: New insights from a conditional nonparametric frontier analysis. *Journal of Applied Econometrics, 30*, 826–847.
Mathijs, E., & Vranken, L. (2000). Farm restructuring and efficiency in transition: Evidence from Bulgaria and Hungary. In *Paper presented at the* American agricultural economics association annual meeting.
McCloud, N., & Kumbhakar, S. C. (2008). Do subsidies drive productivity? A cross–country analysis of Nordic dairy farms. In S. Chib, W. Griffiths, G. Koop, & D. Terrel (Eds.), *Advances in econometrics: Bayesian econometrics: 23* (pp. 245–274). Bingley: Emerald Group Publishing.
Minviel, J. J., & Latruffe, L. (2016). Effect of public subsidies on farm technical efficiency: A meta-analysis of empirical results. *Applied Economics*. doi:10.1080/00036846.2016.1194963.
Nastis, S. A., Papanagiotou, E., & Zamanidis, S. (2012). Productive efficiency of subsidized organic alfalfa farms. *Journal of Agricultural and Resource Economics, 37*(2), 282–288.
Racine, J. S. (2008). Nonparametric econometrics: A primer. *Foundations and Trends in Econometrics, 3*(1), 1–88.
Racine, J. S., & Li, Q. (2004). Nonparametric estimation of regression functions with both categorical and continuous data. *Journal of Econometrics, 119*, 99–130.

Rasmussen, S. (2010). Scale efficiency in Danish agriculture: An input distance-function approach. *European Review of Agricultural Economics, 37*(3), 335–367.

Rizov, M., Pokrivcak, J., & Ciaian, P. (2013). CAP subsidies and productivity of the EU farms. *Journal of Agricultural Economics, 64*(3), 537–557.

Serra, T., & Oude Lansink, A. (2014). Measuring the impacts of production risk on technical efficiency: A state-contingent conditional order-m approach. *European Journal of Operational Research, 239*, 237–242.

Serra, T., Zilberman, D., & Gil, J. M. (2008). Farms' technical inefficiencies in the presence of government programs. *The Australian Journal of Agricultural and Resource Economics, 52*, 57–76.

Serra, T., Zilberman, D., Goodwin, B. K., & Featherstone, A. (2006). Effects of decoupling on the mean and variability of output. *European Review of Agricultural Economics, 33*(3), 269–288.

Silva, E., Arzubi, A., & Berbel, J. (2004). An application of Data Envelopment Analysis (DEA) in Azores dairy farms. *New Medit, 3*, 39–43.

Silva, E., & Marote, E. (2013). The importance of subsidies in Azorean dairy farms' efficiency. In A. B. Mendes, E. Soares da Silva, & J. M. Azevedo Santos (Eds.), *Efficiency measures in the agricultural sector* (pp. 157–166). Dordrecht: Springer.

Silverman, B. W. (1986). *Density estimation for statistics and data analysis*. London: Chapman & Hall.

Simar, L., & Wilson, P. W. (2015). Statistical approaches for nonparametric frontier models: A guided tour. *International Statistical Review, 83*(1), 77–110.

Simar, L., & Wilson, P. W. (2011). Two-stage DEA: Caveat emptor. *Journal of Productivity Analysis, 36*, 2005–2018.

Sipiläinen, T., Kumbhakar, S. C., & Lien, G. (2014). Performance of dairy farms in Finland and Norway from 1991 to 2008. *European Review of Agricultural Economics, 41*(1), 63–86.

Sipiläinen, T., & Oude Lansink, A. (2005). Learning in organic farming – An application on Finnish dairy farms. In *Paper presented at the XIth congress of the European association of agricultural economists (EAAE)*.

Skevas, T., Oude Lansink, A., & Stefanou, S. E. (2012). Measuring technical efficiency of pesticides spillovers and production uncertainty: The case of Dutch arable farms. *European Journal of Operational Research, 223*, 550–559.

Su, L., Chen, Y., & Ullah, A. (2009). Functional coefficient estimation with both categorical and continuous data. In Q. Li, & J. S. Racine (Eds.), Nonparametric econometric methods, advances in econometrics*: 25* (pp. 131–167). Bingley: Emerald Group Publishing Limited.

Trnková, G., Malá, Z., & Vasilenko, A. (2012). Analysis of the effects of subsidies on the Economic behavior of agricultural businesses focusing on animal production. *Agris On-line Papers in Economics and Informatics, 4*(4), 115–126.

Tzeremes, N. G. (2015). Efficiency dynamics in Indian banking: A conditional directional distance approach. *European Journal of Operational Research, 240*, 807–818.

Yotopoulos, P. A. (1967). From stock to flow capital inputs for agricultural production functions: A microanalytic approach. *American Journal of Agricultural Economics, 49*(2), 476–490.

Zhu, X., Karagiannis, G., & Oude Lansink, A. (2011). The impact of direct income transfers of CAP on Greek olive farms' performance: Using a non-monotonic inefficiency effects model. *Journal of Agricultural Economics, 62*(3), 630–638.

Zhu, X., & Oude Lansink, A. (2010). Impact of CAP subsidies on technical efficiency of crop farms in Germany, the Netherlands and Sweden. *Journal of Agricultural Economics, 61*(3), 545–564.