



Efficiency in the European agricultural sector: environment and resources

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Abstract

This article intends to compute agriculture technical efficiency scores of 27 European countries during the period 2005–2012, using both data envelopment analysis (DEA) and stochastic frontier analysis (SFA) with a generalized cross-entropy (GCE) approach, for comparison purposes. Afterwards, by using the scores as dependent variable, we apply quantile regressions using a set of possible influencing variables within the agricultural sector able to explain technical efficiency scores. Results allow us to conclude that although DEA and SFA are quite distinguishable methodologies, and despite attained results are different in terms of technical efficiency scores, both are able to identify analogously the worst and better countries. They also suggest that it is important to include resources productivity and subsidies in determining technical efficiency due to its positive and significant exerted influence.

Keywords Agriculture resources productivity · European subsidies · Common agricultural policy (CAP) · Data envelopment analysis (DEA) · Stochastic frontier analysis (SFA) · Generalized cross-entropy (GCE)

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Introduction

Belonging to the primary sector of any economy, agriculture is imperative in economic, social, territorial, resource, and environmental terms. Since human welfare depends over the amount and stability of agricultural production (measured by crop yield and cultivated area (Garibaldi et al. 2011)), this sector will continue to play, as played previously, a vital role for humanity, turning significant the analysis of its efficiency.

Economic efficiency may be divided into technical efficiency and allocative efficiency, where technical efficiency translates into the ability of a production unit in reaching the maximum output given the set of inputs and the production technology used. Whereas allocative efficiency reflects the ability of a production unit to use the inputs in optimal and efficient proportions, given their prices and the production technology used. As long as we have heterogeneity in levels of development of agricultural European regions and in their agriculture productivity, it turns relevant the analysis and evaluation of technical efficiency in the agriculture sector in Europe. Moreover, the proposed schedule for 2014–2020 by the Common Agricultural Policy (CAP) attempts to launch a set of recommendations to ensure the optimization of inputs efficiency used in the agricultural production and livestock process.

In most of the developing countries, increases in agriculture productivity and technical efficiency are very important policy goals, since it is one of the main sources of overall economic growth (Zamanian et al. 2013). Recent studies on agricultural technical efficiency yield useful information for policymakers by founding the possibility of increasing economic activity, namely output, without increasing resource use or developing new cleaner technologies, whose principal purpose is to reduce greenhouse gases (GHG), specifically under Kyoto Protocol (Robaina-Alves and Moutinho 2014; Toma et al. 2017). As such, studies about the productive performance of the European agriculture sector will help policy makers to realize the existent potential for improving it, as well as to expand production under recent CAP reforms. These yield recent changes that have created new conditions for increasing not only direct income support to European farmers but also to predict other reforms consequences like those related to the environment.

To measure technical agricultural efficiency, different methodologies and strategies have been proposed. Some authors such as Zhao and Chen (2014), Robaina-Alves and Moutinho (2014), Kočíšová (2015), Vlontzos et al. (2017), and Toma et al. (2017) all used decomposition techniques, such as index decomposition analysis (IDA) or Log-mean Divisia Index (LMDI) through data envelopment analysis (DEA). Other studies compare outcomes from parametric and non-parametric techniques (Hoang and Alauddin 2012; Picazo-Tadeo et al. 2012; Hoang and Trung 2013; Khoshnevisan et al. 2014, among others).

Important measures for technical and allocative efficiency are those of Farrell (1957), but different others emerged to calculate and estimate the efficient frontier in terms of farm performance and efficiency measurement. Methodologies developed involve parametric (econometric) and non-parametric (mathematical programming) approaches. In the first, the functional form of the efficient frontier is imposed a priori, while in the last the frontier is computed based on sample observations. Both approaches have strengths and weakness and their main difference relies upon the assumption used to estimate the frontier. The parametric approach main strength relies on a stochastic frontier that allows noise effect to be separated from the inefficiency ones. Nevertheless, it requires the specification of a functional form, thus implying structural restrictions allowing that misspecification effects of the functional form to be baffled with inefficiency. Moreover, parametric models can be deterministic or stochastic. The former assumes that any deviation from the frontier is due to inefficiency while the latter allows statistical noise. In the non-parametric approach, the opposite is true provided it is free from the misspecification of the functional form or any other restrictions, but it does not allow to account for statistical noise being thus vulnerable to outliers (Kwon and Lee 2004; among others).

Taking into account the considerations described above, the goals and distinguishing features of this article are exposed

next. The first goal is to estimate the technical agricultural efficiency of European countries. For this, two different techniques are applied and compared. It is used a DEA approach and a stochastic frontier analysis (SFA) with the generalized cross-entropy (GCE) estimator (e.g., Golan et al. 1996), a recent approach that combines information from DEA and the structure of composed error from traditional SFA with maximum likelihood (ML), without requiring distributional assumptions. Although there have been quite a large number of studies on technical agricultural efficiency, there is scarce literature using SFA with GCE to assess technical efficiency. Second, we want to realize which factors explain technical efficiency differences. For that, it is proposed a dynamic efficiency analysis by using the parametric econometric quantile approach. The dependent variable is the estimated score of technical efficiency and the explanatory variables are resources productivity, domestic material consumption, bovine population, crops products, share of total organic crop area out of total used agricultural area, subsidies over crops output products, and subsidies on animal output products. More recently, Minviel and Latruffe (2017) found that subsidies are commonly negatively associated with farm technical efficiency, looking at empirical studies. When using the quantile regression approach, we have the possibility of estimate the effects of the conditional technical efficiency distribution. It also turns possible to examine determinants of technical efficiency deployment all over the conditional distribution, with emphasis over determinants of technical efficiency take-off. The choice of these quantiles results from the distribution of technical efficiency scores delivered by the two optimization solution problems employed.

In summary, the relevance and innovation of this article is related to (i) estimating and comparing the efficiency of agricultural sector of countries, which is as referred, very relevant, but in particular to do so with an innovative method, such as SFA with GCE; (ii) the fact of joining in the same study two steps, in which the second one uses the scores estimated in the first one to know what affects the efficiency of the countries; and (iii) the fact of innovating by doing this second step with general fixed effects and with estimates by quantile, that allows to differentiate effects in more efficient countries and less efficient countries.

The rest of the article develops as follows. The “[Literature review](#)” section presents a brief literature review, while “[Data and methodology](#)” section describes the data and methodologies used. “[Results and discussion](#)” section presents the attained results and discusses their main implications, while “[Conclusions](#)” section concludes this work.

Literature review

There is an extensive literature on measuring efficiency using DEA and SFA. Efficiency is analyzed considering the

existence of desirable and/or undesirable outputs of production, where environmental negative effects are seen as undesirable (Färe et al. 2004 and Zhou et al. 2006, 2007). DEA has been applied to studies of various agricultural products from horticulture, to cotton and to aquaculture (for example, Sharma et al. 1999a; Iraizoz et al. 2003; Reinhard et al. 2000; Fousekis et al. 2001; Arita and Leung 2014; Iliyusu et al. 2016). Other studies use DEA applied to other sectors, as the one of Chen and Jia (2017) that evaluate the environmental efficiencies of China's industry using data from 2008 to 2012. The authors demonstrate that apart from several developed provinces, the environmental efficiencies of China's industry are generally low and that larger differences exist in environmental efficiencies between the regions in China, suggesting that government attention is needed considering the unbalanced development of its regional industry. In forestry, Li et al. (2017) performed a cross-sectional dataset analysis using DEA to investigate the forestry resources efficiency in 31 inland provinces and municipalities of China in years 2008, 2012, and 2013. Afterwards, they use the Malmquist total factor productivity index method, whereas the innovation of the article lies in the dynamic process of analysis.

Other empirical applications include the SFA model, for example, Abdulai and Huffman (2000) on rice farmers in Northern Ghana, Bravo-Ureta and Evenson (1994) on peasant farmers in eastern Paraguay, Chen and Huffman (2006) using a county-level dataset of China, and Xu and Jeffrey (1998) on a cross-section of Chinese farm households. Other studies show the estimation of a parametric production function using SFA, but most focus over a single country's agricultural sector. Thus, the comparative analysis of technical efficiency is rather scarce (despite the exceptions of Barnes et al. 2010 and Zhou and Lansink 2010).

Both DEA and SFA models are also used to identify different levels of environmental efficiency of agricultural systems. They consider as inputs nutrients, nitrogen, and phosphorous, whose analysis revealed these as relevant factors to explain emissions on farms and livestock. These studies include Reinhard et al. (2002), Abay et al. (2004), Hoang and Coelli (2011), and Hoang and Alauddin (2012). Coelli et al. (2012) investigate the environmental performance of 117 pig farms in Belgium using a DEA non-parametric technical analysis. Using both DEA and SFA, Lauwers (2009) and Van Meensel et al. (2010) recognize the existing trade-off between environmental effectiveness and economic efficiency using the Coelli et al. (2012) data.

Other authors advocate that agriculture efficiency should be evaluated considering the principle of balance of materials: as cost allocative efficiency, fertilizer consumption intensity, the size of land, and the share of owned land out of total land (for example, Van Passel et al. 2009; Lauwers 2009; Van Meensel et al. 2010; Hoang and Coelli 2011; Picazo-Tadeo et al. 2012; Hoang and Alauddin 2012; Hoang and Trung

2013; Khoshnevisan et al. 2014, among others). Xiao et al. (2017) built a theoretical model on how farmland conversion affects economic growth. They empirically analyzed the optimal scale of farmland conversion by using both dynamic and threshold regressions based on panel data of 31 Chinese provinces from 1997 to 2013.

Other studies on agriculture focus on the influence of personal characteristics such as age, education, experience and specialization, or physical aspects such as farm size and certain input usage (Sharma et al. 1999b; Fousekis et al. 2001; Iraizoz et al. 2003). In another strand of reviewed studies, the environmental assessment was made through the efficient use of natural resources and nutrients. They found that agricultural production is limited by the restriction of low topsoil fertility (due to scarcity of water and nutrients, especially in Africa), as reported in Giller et al. (2006), among others.

Using 196 rice farms in South Korea, Nguyen et al. (2012) investigated the environmental performance based on the Material Balance theory. Results point for a high variability in the coefficients associated with the explanatory drivers of environmental efficiency in all farms. Avadí et al. (2014) use a combination of life cycle assessment (LCA) and DEA to examine the eco-efficiency in 13 fleet segments of fishing vessels and Zhu et al. (2014) applied the same combined methodology to compare the eco-efficiency of 10 pesticides. Arita and Leung (2014) use the DEA approach, considering as inputs labor, land, machinery, and other expenses, and as outputs total sales generated from production. The author's results showed that only 12% of the farms in 2007 may be classified as efficient, with a steady decline in efficiency over time.

Bojnec et al. (2014) studied the level of technical efficiency (using DEA) in ten new EU Member States during the period 2001–2006. Despite time and countries results variability found, the authors evidence efficiency scores below 1 for all countries. They suggest that these differences imply future opportunities for the better use of agricultural resources. Hoang and Rao (2010) evaluated the efficiency of the agricultural sector of 29 OECD countries. The goal was to define potential traces that ensure the capacity to reach a sustainable agricultural production. Empirical applications allowed them to conclude that OECD has the potential to save 72.3% of cumulative exergy consumption. Moreover, it was argued that improvements can be achieved by improving technically efficient and by doing a better inputs combination choice. Furthermore, they argue that the sustainable efficiency varied enormously across countries and that efficiency levels in 2003 were lower than in 1990.

Špicka (2016) evaluates the change in the energy efficiency of crop production in 24 EU countries during the period 2002–2012. The change in the energy efficiency in time was calculated through the Malmquist index, identifying the UK, Portugal, and Sweden as countries with the most dynamic positive change in energy efficiency. By opposition, Baltic States and Poland experienced the most dynamic decline of

energy efficiency. For crop output and the EU sample also, Kočíšová (2015) concludes that in inefficient agricultural sectors to have efficient production of a given quantity of output it was necessary to reduce the value of the input labor by 6.18%, total utilized agricultural area by 14.45%, and total assets by 5.93%. Moreover, in the case of the output-oriented model, results point that the agricultural sectors should produce 111.85% of their crop output and 113.41% of their animal output. Using also the EU sample, Vlontzos et al. (2014) evaluate the energy and environmental efficiency of the primary sectors of the EU member state countries. The study is based on a non-radial DEA model which allows for non-proportional adjustments to energy inputs and undesirable outputs. Results pointed that Eastern European countries achieved low efficiency scores, an expected result due to low technology level being implemented in the primary production process. Finally, Hoang and Alauddin (2012) present a DEA framework oriented to inputs which allows the measurement and decomposition of economic, environmental, and ecological efficiency levels in agricultural production across 30 OECD countries. The optimal input combinations performed, in order to minimize total costs, were total amount of nutrients, and total amount of cumulative exergy contained in inputs. Results reveal a significant scope to make agricultural production systems more environmentally and ecologically sustainable, just by being more technically efficient and by changing the input combinations.

Using the EU agricultural sector, also we have more recent studies using DEA techniques. Kočíšová (2015) investigates the relative technical of the agricultural sector in the EU using DEA during 2007–2011. Results allowed the author to conclude that EU agricultural sectors performed efficiently, having changed over the last years, where efficiency seems to have decreased through time. Toma et al. (2017) examine the agricultural efficiency of EU countries, through a bootstrap-DEA using data of labor, land, capital, fertilizers, and irrigation area, during 1993–2013. Results seem to indicate that oldest EU countries have a more efficient and optimized crop production with respect to resource savings and output maximization, maybe due to the CAP. The authors suggest that attention should be given to the maximization of agricultural production as well to the environmental resource overexploitation. Vlontzos et al. (2017) build a synthetic Eco-(in) efficient index by using a directional distance function-DEA model to study the sustainability of the EU agricultural sector for the period 1999–2012. They use this to study the Environmental Kuznets Curve allowing them to conclude that more sustainable production practices at the country level are not totally connected with its economic development provided that Eco-(in) efficiency and GDP levels of EU countries seem to be linked with an N-shaped curve.

Data and methodology

Data

We use data for the time period 2005–2012 for 27 European countries¹, collected from Eurostat and with respect to the agriculture sector. Energy consumption, in Economic Accounts for Agriculture, data was collected in millions of Euros at constant 2005 prices. Net value added was also collected from this database at constant 2005 prices, in million euros. Net value added refers to the value of output less the values of both intermediate consumption and consumption of fixed capital². Data of agricultural area in 1000 ha was collected from the Regional Agriculture Statistics, representing land used from the NUTS 2 regions folder. From the Agriculture Labor Input Statistics, we collected data for the total labor force input in 1000 annual work units.

We have used as output the net value added and as inputs labor force, utilized agricultural area, and energy consumed in the technical efficiency estimation, variables frequently considered in the production function estimation for the agricultural sector (see for instance Iraizoz et al. 2003 or Toma et al. 2015). For quantile regressions, the dependent variable considered was the estimated score of technical efficiency and the independent variables were chosen attending the data availability at Eurostat and by the relevance they might have on affecting technical efficiency: (i) domestic material consumption (DMC)³; (ii) resources productivity (gross domestic product divided by DMC); (iii) bovine and pig population (in thousand heads—animals), separately; (iv) organic crop area (hectare); (v) subsidies on product cereals (millions Euros); (vi) subsidies on product animals (millions Euros); and (vii) crop products (cereals for the production of grain by 1000 ha area cultivation).

Common agricultural policies have had implication adjustments in the agricultural sector, namely in production. So, a policy based over subsidies support would be a strong instrument to affect their weak efficiency and we should expect a positive and significant effect of these over technical efficiency.

¹ Belgium, Bulgaria, Czech Republic, Denmark, Germany, Estonia, Ireland, Greece, Spain, France, Italy, Cyprus, Latvia, Lithuania, Luxembourg, Hungary, Malta, Netherlands, Austria, Poland, Portugal, Romania, Slovenia, Slovakia, Finland, Sweden, and United Kingdom.

² For this sector in particular, it includes de net value added of all units involved in agricultural production, also if the units have more economic important activities as well and if the purpose of the units is not commercial. Kitchen garden (producing for own consumption only) is not included. The data considers: growing of non-perennial crops; growing of perennial crops; plant propagation; animal production; mixed farming; support activities to agriculture and post-harvest crop activities; hunting, trapping and related service activities.

³ In tonnes per capita. Considering only biomass, DMC measures the total amount of biomass directly used by the economy, being defined as the annual quantity extracted from the domestic economy, plus all physical imports minus all physical exports.

However, there is empirical evidence that the direction (significantly negative, significantly positive, or non-significant) of the observed effects is sensitive to the way subsidies are modeled (Minviel and Latruffe 2017). In fact, subsidies may have both positive and negative effects on efficiency and productivity through the income effect. We may expect subsidies to increase technical efficiency if they are used by farmers as the necessary financial means to keep technologies up to date or if farmers use these to invest into efficiency improvements on farm organization. However, we could also expect the opposite effect (increasing subsidies decrease technical efficiency) if farmers are less motivated to improve despite the higher income received due to subsidies. In quantile regression analysis performed afterwards, we have used two subsidy-related variables to capture the impacts of different types of subsidies over technical efficiency. The first is the share of crop subsidies in total subsidies, which is assumed to reflect the degree of decoupling and the second is the degree of subsidy dependence and specialization (share of animal products subsidies over total subsidies, assumed to reflect the degree of coupling). This kind of subsidies has also been used by Zhu et al. (2012) exploring technical efficiency in German, Dutch, and Swedish dairy farms. It should also be noticed that total subsidies from the CAP are considered as non-stochastic income sources. In this sense, it may influence farmers' decision of production both by the income/wealth and insurance effects.

Moreover, biomass consumption in this sector is also expected to impact technical efficiency differentials provided that domestic consumption of this material is an important resource in the sector as well as the resources productivity used in the sector. Also the different levels of technical efficiency may be explained by the different levels of animal production and other output products of the sector. Moreover, all these factors may contribute positively and negatively to sustain the regression expected coefficient signs and guarantee robustness in the distribution of the technical efficiency levels. The statistical relevance of some of these variables may help us to understand for which efficiency levels there exists or not an impact (Bilgili et al. 2016; Qureshi et al. 2016). For example, do production subsidies with respect to animals or crops affect significantly the agricultural sector in European countries in the same sense and magnitude, or should we expect that a specific kind of subsidy affects positively the sector in countries with higher technical efficiency, while others affect countries with lower technical efficiency levels? Quantile regression results would help us to conclude into these different directions.

Methodology

The methodology followed consists in two different steps. In the first, it is computed technical efficiency through the DEA

and SFA with GCE, and in the second a quantile regression approach is followed. This two-phase methodology is often used as a way of realizing that factors other than those that typically enter into the production function condition production efficiency. As examples, it can be pointed McDonald (2009) and Hoff (2007).

Technical efficiency

Technical efficiency is a crucial tool to measure a production unit performance, by comparing the observed output and the potential output of a production unit. There are several methods that can be used to predict technical efficiency, being DEA and SFA the most dominant in the efficiency analysis literature. SFA is accomplished in this study using the GCE estimator (e.g., Macedo and Scotto 2014; Robaina-Alves et al. 2015). Considering the usual stochastic frontier model (e.g., Kumbhakar and Lovell 2000) $\ln(y) = f(X; \beta) + v - u$, the reparameterizations of the $(K \times 1)$ vector β and the $(N \times 1)$ vector v follows the same procedures as in the traditional maximum entropy estimation (e.g., Golan et al., 1996): $\beta = Zp$, with Z being a $(K \times KM)$ matrix of support points, p a $(KM \times 1)$ vector of unknown probabilities; and $v = Aw$, with A a $(N \times NJ)$ matrix of support points and w $(NJ \times 1)$ a vector of unknown probabilities. For the inefficiency error component, vector u , the reparameterization is similar to that of v , taking only into account that u is a one-sided random variable, which implies that the lower bound for the supports (with $2 \leq L < \infty$ points) is zero for all error values: $u = B\rho$, with B a $(N \times NL)$ matrix of support points and ρ a $(NL \times 1)$ vector of unknown probabilities. Further details may be obtained from Campbell et al. (2008), Macedo and Scotto (2014), and Macedo et al. (2014).

In this study, the supports in Z are defined through $[-10, 10]$, being this a conservative choice. Provided that vector v is a two-sided random variable representing noise, supports in matrix A are defined symmetrically and centred on zero, using the three-sigma rule with the empirical standard deviation of the noisy observations. The supports in matrix B are defined in the range $[0, -\ln(\text{DEA}_n)]$, where DEA_n represents the lower technical efficiency estimate obtained by DEA in the sample (e.g., Macedo and Scotto 2014; Robaina-Alves et al. 2015). DEA uses linear programming to construct a non-parametric piecewise linear production frontier, using output- and input-orientations, different return to scales technologies, and the possibility of multiple inputs and multiple outputs. The efficiency measures are then computed relative to the production frontier; e.g., Coelli et al. (2005). In this study, an output-oriented model under constant returns to scale is considered to provide the lower technical efficiency estimate that is needed for the supports in maximum entropy estimation. It is important to note that DEA is used in SFA with maximum entropy only to define an upper bound for the supports, which means that the main criticism on DEA (it does not account for noise; all deviations

Table 1 Performance of countries—resume of results of DEA and SFA estimations

Our results period: 2005–2012		Kočišová (2015) period: 2007–2011	Bojniec et al. (2014) period: 2001–2006	Akande (2012) period: 1999–2009	Hoang and Rao (2010) and Hoang and Coelli (2011) period: 1990–2003	Vlontzos et al. (2014) period: 2001–2008				
Best	Worst	Best	Worst	Best	Worst	Best	Worst	Good performers	Best	Worst
Cyprus	Czech Republic	Belgium	Poland	Bulgaria	Baltic States	West European region	Northern European region	Belgium, Luxembourg	Denmark	Germany
Denmark		Denmark	Slovenia	Hungary					France	Sweden
France	Hungary	Finland		Slovakia	Poland			Netherlands	Ireland	
Italy	Ireland	France						Denmark		
Luxembourg	Latvia	Greece								
Greece	Lithuania	Hungary								
Malta	Poland	Ireland								
Netherlands	Slovakia	Italy								
Spain	Slovenia	Malta								
UK	Sweden	Netherlands								
	Belgium	Romania								
	Bulgaria	Slovakia								
		Sweden								

Note: own elaboration

from the production frontier are estimated as technical inefficiency) is used in this context as an advantage (a worst case scenario to establish the bound for the supports in maximum entropy estimation). Thus, given this feature, a constant returns to scale model is used here because it provides technical efficiency scores that are lower than or equal to those from a variable returns to scale model.

The GCE estimator⁴ in the SFA context is given by $\text{argmin} \left\{ p' \ln \left(\frac{p}{q_1} \right) + w' \ln \left(\frac{w}{q_2} \right) + \rho' \ln \left(\frac{\rho}{q_3} \right) \right\}$, p, w, ρ subject to the model constraint, $\ln(y) = XZp + Aw - B\rho$, and the three additivity constraints, $\mathbf{1}_K = (I_K \otimes \mathbf{1}'_M) p$, $\mathbf{1}_N = (I_N \otimes \mathbf{1}'_J) w$ and $\mathbf{1}_L = (I_L \otimes \mathbf{1}'_L) \rho$, where \otimes represents the Kronecker product. In all the matrices, five points in the supports are considered. The vectors q_1 and q_2 in the objective function are non-informative, and the non-uniform vector q_3 is specified in this study as $q_3 = [0.40, 0.30, 0.15, 0.10, 0.05]$ for each observation, where the cross-entropy objective shrinks the posterior distribution in order to have more mass near zero, following the usual beliefs in the traditional ML estimation (e.g., Kumbhakar and Lovell 2000, p. 74).

Quantile approach

In the second part of our study, we perform regression analysis to find the determinants of efficiency. For that, we use quantile regressions due to the limitations pointed by Simar and Wilson (2007) and Zelenyuk and Zheka (2006) to the traditional Tobit estimator. They argue that by using it, regression analysis of efficiency determinants is inappropriate by failing to address the dependency problem of DEA efficiency scores.

⁴ The code was implemented by us in MATLAB (R2009a) software.

Also, if we use standard linear regression techniques, we may only attend for a partial relationships. However, we could be interested in describing variables relationship at different and specific points in the conditional distribution of the dependent variable. Quantile regression offers that possibility and has been used in studies for the willingness to pay for the reduction of both air and noise pollution (O’Garra and Mourato 2007) and of the impacts of soil contamination and urban development (Schreurs et al. 2014). Quantile regressions advantages include its robust properties, even in the absence of normality, and its power to estimate effects at specific and different points of the conditional dependent variable (outcome) distribution (O’Garra and Mourato 2007). Heteroskedastic robust estimates are ensured by robust standard errors reported in fixed effects estimates. The number of bootstrap repetitions are inversely related to the sample size and we do not report Koenker and Basset standard errors, but bootstrap standard errors (Koenker and Basset 1982) using 1000 bootstrapping repetitions.

Results and Discussion

In a first stage, we focus on the analysis and interpretation of results about scores and changes on the countries technical efficiency ranking through the time period.

In appendix, we present the detailed score results for DEA and SFA with the GCE estimator (see Tables 3 and 4). SFA results are more robust as compared to DEA, and with this method we never get an efficiency score of 1. Despite the fact that DEA and SFA are very distinct methodologies, it is interesting to notice that although technical efficiency values are different between both techniques, both identify analogously

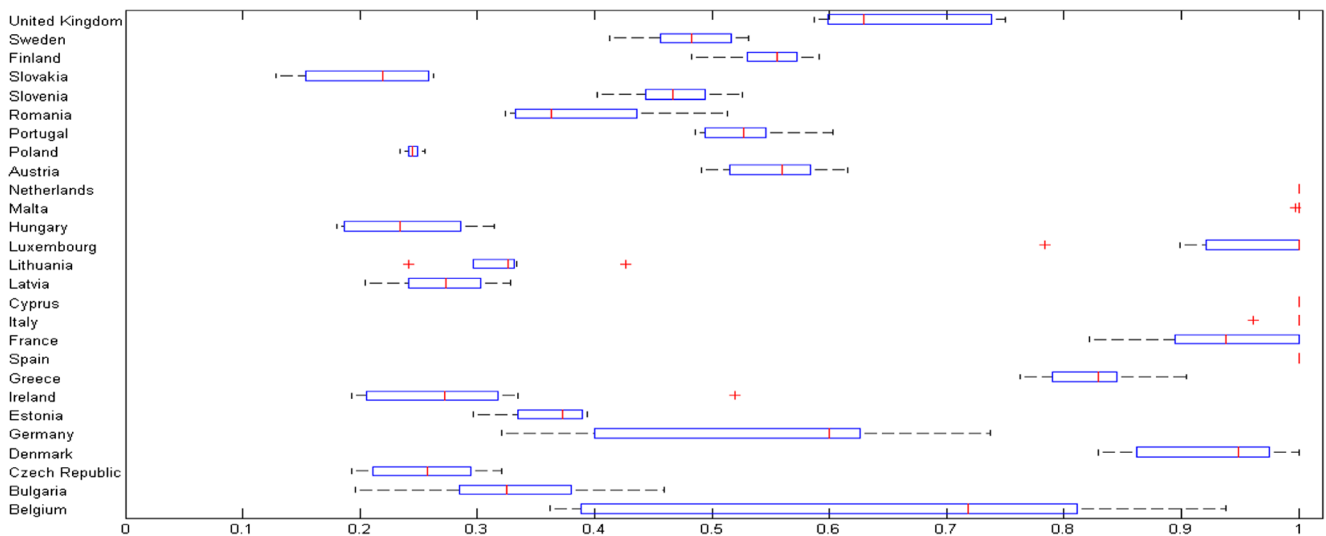


Fig. 1 DEA efficiency estimates in 2005–2012

the worst and best countries. This can also be checked in Table 5 in appendix that presents a summary of the sixth highest and lowest scores of technical efficiency for each year in the sample and using both DEA and SFA with GCE (countries in red are those that change provided one or the other method used). Specification and diagnosis tests are presented in Table 6 at the appendix and results justify the choice of quantile regressions in the second stage.

In Table 1 is presented a resume of general results for both techniques, and the results of other studies for comparison purposes. As it can be seen, our results corroborate most of the results of previous studies, concerning the good and bad performances of European countries agricultural sector.

Figures 1 and 2 shows graphically the efficiency position and evolution of countries for both methodologies.

We can observe that almost all countries reduced their efficiency in this period, result also pointed by Kočíšová (2015). For example, the scores for Germany, Ireland, and Belgium, in 2012, are only half (or even less than half) of their scores in 2005. There are some exceptions as the case of Estonia and Finland, which improved their efficiency score.

In a second stage, a parametric approach through the use of quantile regressions is used, applied to the efficiency scores obtained previously as a dependent variable, to explain the different levels of technical efficiency across countries.

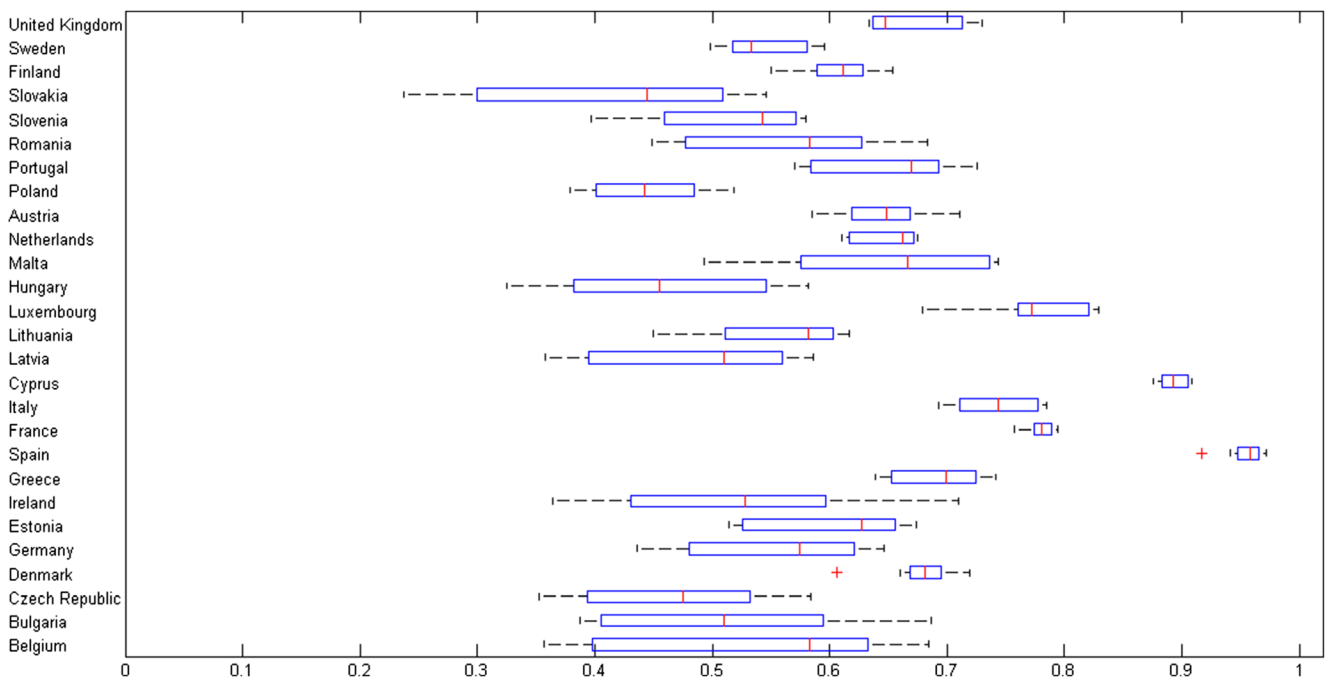


Fig. 2 SFA with GCE efficiency estimates in 2005–2012

Table 2 Results of fixed effects and quantile regression estimates (SFA with GCE method)

Independent variables	FE-VCE	Quantile regression				
		Q (0.10)	Q (0.25)	Q (0.50)	Q (0.75)	Q (0.90)
DMC (Biomass)	-0.00	-0.00	-0.00	-0.00**	-0.00**	-0.00
Resource productivity	-0.04	0.23*	0.21*	0.22*	0.30*	0.32*
Crops products	0.00	-0.00	0.00	0.00	-0.00	0.00
Organic crop area	-0.016*	-0.00	-0.00	-0.00	-0.01*	-0.02*
Subsidies on product cereals	-0.00	0.00	-0.00	-0.00	0.00**	0.00**
Subsidies on product animals	0.00	0.00**	0.00**	0.00*	0.00	0.00
Pig population	0.00	0.00	0.00*	0.00*	0.00*	0.00***
Bovine population	0.00*	-0.00	0.00	-0.00	-0.00	-0.00
Constant	0.40**	0.01	0.15*	0.23*	0.36*	0.58*
R^2 /pseudo R^2	0.25	0.22	0.34	0.42	0.35	0.25

Notes: Dependent variable: scores of efficiency (based on the SFA model). FE-VCE stands for fixed effects with robust standard errors. *, **, *** mean significant at 1, 5, and 10%, respectively. The number of observations refers to the total N in our sample = 216

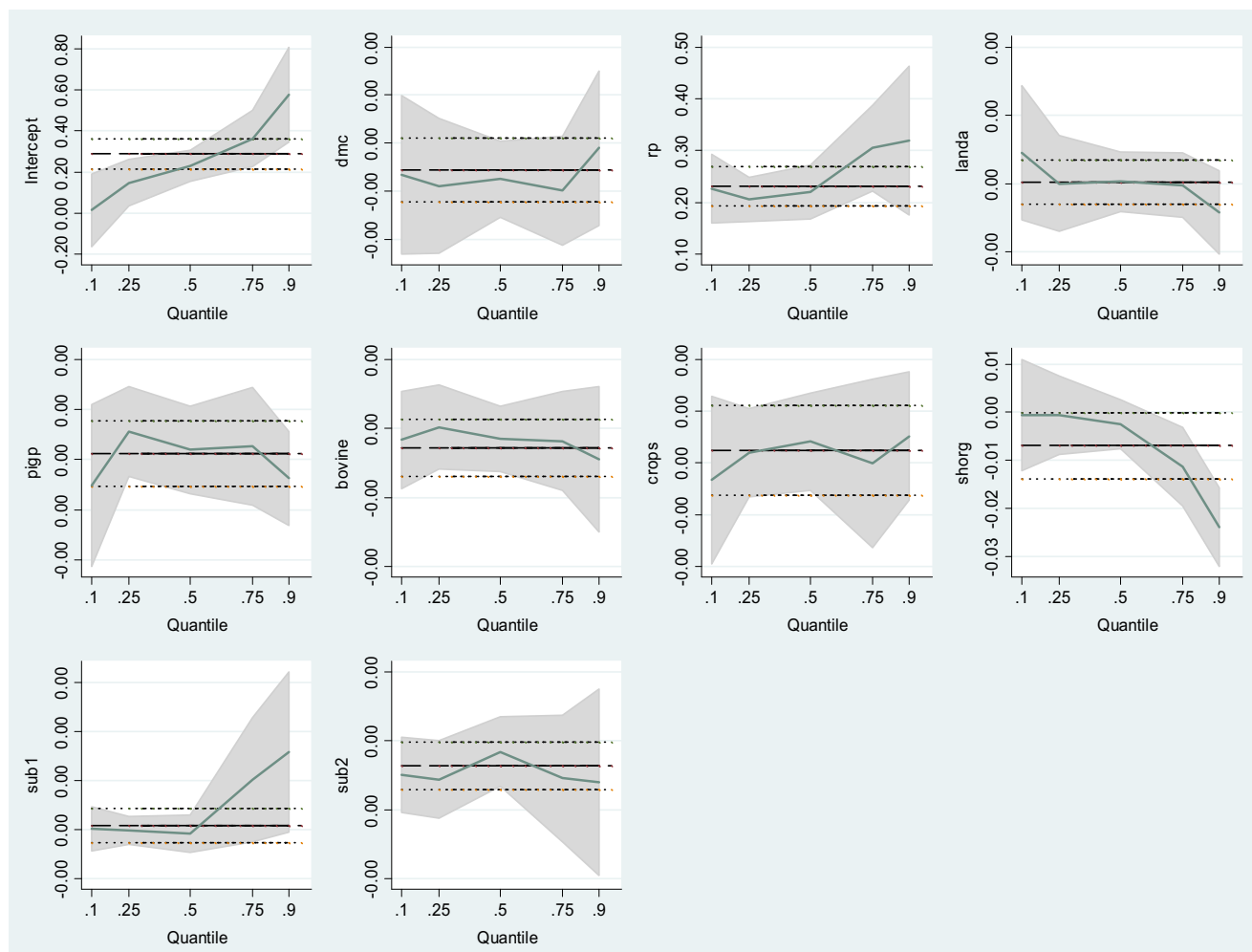


Fig. 3 Plot of fixed effects quantile regression—SFA with GCE results. Note: this plot shows how the effects of each regressor vary over different quantiles and how the magnitude of the effects at these different quantiles

would differ considerable from the fixed effects estimations. Plots performed using Stata software

According to Table 2, the estimates from fixed regression using the SFA-GCE show a positive and significant influence of bovine population and a negative and significant influence of the share of organic crop area out of total used agricultural area over technical efficiency⁵ (the results from fixed regression using DEA are presented in Table 7 in the appendix for robustness check).

Resource productivity shows a positive and significant influence on technical efficiency, and its estimated coefficients are higher in upper quantiles. As such, we may conclude that the positive relationship between technical and resources productivity has a greater magnitude when considering the upper levels of cross-country technical efficiency distribution, when compared to the results obtained by considering the central tendency of technical efficiency distribution. This increase in estimated parameters shows the importance of resources productivity in determining technical efficiency when considering countries with higher technical efficiency scores (in the upper quantiles of technical efficiency distribution). Increasing resources productivity could then provide higher technical efficiency scores.

There is a negative and significant influence of domestic material consumption (biomass) (for median quantiles, i.e., 50th and 75th quantile). In the lower quantiles (10th and 25th), the negative relationship between technical efficiency and domestic materials consumption is not statistically significant. As such, it seems that for median efficiency scores, domestic materials consumption reduces technical efficiency. However, progressing up the technical efficiency, we observe that the magnitude of this relationship gets bigger. This may seem intuit and possible to be attributed to learning curves.

There is a negative and significant influence of share of organic crop area out of total used agricultural area (for 75th and 90th quantile) and a positive and significant influence of pig population over SFA-GCE technical efficiency scores.

It is also found that by moving up on the technical efficiency distribution (considering 75th and 90th quantiles), results are considerably different from those obtained in other quantiles, where there are significant positive relationships between technical efficiency and subsidies over crops outputs (Sub 1) and subsidies on animals' output products (Sub 2). However, for different quantiles, these relationships are only statistically significant for the upper quantiles (75th and 90th) and for the lower quantiles of the technical efficiency distribution (10th, 25th, and 50th), respectively, which do not go into the direction of Minviel and Latruffe (2017) results.

All previous results in both methodologies and in the first and second estimation stages claim for some important political and practical implications. Factors like subsidies on crops products and subsidies on animals output products,

resources productivity, and domestic materials consumption simultaneously allow to explain differences in technical efficiency in the European agricultural sector. Results obtained make sense as the productivity of resources has a positive influence on the score of technical efficiency. In fact, resource productivity measures how efficiently natural resources are used by the sector and indicates whether economic growth is compatible with a more efficient use of the natural resources. Animal output subsidies also show a positive influence that can be explained by the coupling between these subsidies and production, which encourages their application in more efficient production processes. On the other hand, crop subsidies have a negative influence, especially on the higher efficiency quantiles, which may be related to the decoupling of these subsidies. As such, our results contradict those of Zhu et al. (2012) where the authors also use subsidy-related variables⁶ to reflect the wealth and insurance effect and the coupling effect of CAP subsidies. Their results indicate that a higher degree of coupling in farm support negatively affects farm efficiency, and that the motivation of farmers to work efficiently is lower when they depend on a higher degree of subsidies as a source of income. The authors' finish the article arguing that it is questionable whether farm income support of CAP since the 1992 CAP reform is suitable to achieve its goal to increase farmers' overall competitiveness by improving their efficiency. Our results state that both resources productivity and subsidies do increase technical efficiency, although not all subsidies have the desired complete effect, only helping those in the lowest efficiency scores, like subsidies on animals' outputs.

Moreover, results obtained through quantile regressions corroborate, at least partially, the findings of Zhu and Lansink (2010) which have concluded that total subsidies due to the income and insurance effect are expected to have a negative impact over technical efficiency of crop farms in Germany, Netherlands, and Sweden. However, we need to emphasize that the reliability of the estimated results depends over theoretical consistency of the underlying production technology. As such, caution is needed while interpreting results because we were unable to check all regularity conditions. Besides, we have also not accounted for the effects of changes in the output mix within crop aggregates, provided that diverse products are counted even for specialized crop farms.

The share of organic crop area has a negative influence on efficiency, which may at first appear strange. But in fact, organic farming is a method of production, which puts the highest emphasis on environmental protection and, with regard to livestock production, animal welfare considerations. It

⁵ See Wasserstein and Lazar (2016) for an important discussion on the use of p values.

⁶ The authors use the share of livestock subsidies in total subsidies (%), the share of the sum of subsidies on crops, intermediate consumption and external factors in total subsidies (%), and the share of total subsidies in total farm income (%).

avoids or largely reduces the use of synthetic chemical inputs such as fertilizers, pesticides, additives, and medical products. This organic production may be not so “advanced” in productivity as the “traditional” methods, which may negatively affect efficiency.

Following Baum (2013), graphs in Fig. 3 illustrate how the effects of each regressor vary over different quantiles and how the magnitude of the effects at these different quantiles would differ considerable from the fixed effects estimations. This happens also in terms of the confidence interval around each coefficient. Figure 3 results show that for the lowest quantiles of the conditional scores of efficiency distribution, the coefficients on experience are very low, close to zero. This suggests that the efforts taken by countries in terms of agricultural experience are barely recognized in the European agricultural sector. However, as we move up over the conditional distribution, the coefficient rises significantly especially at the extreme upper quantiles. For countries with the highest scores, on the one hand, additional efforts at resources productivity results in relatively larger increases in the share of total organics crop area out of total used agricultural area. On the other hand, subsidies on crops and subsidies on animal output products additional efforts results in gains in agricultural added value.

Evidence found in both methodologies employed may be explained by the considerable changes in technical efficiency after the implementation of the new CAP (Bartolini and Viaggi 2013). The subsidy policy had effects on energy and environmental efficiency levels of the new Member States as compared to the older Member States, as also mentioned by Hoang and Rao (2010) and Vlontzos et al. (2014). However, these differences are also owed to the low level of technology, which has been implemented into the agricultural production process, being even more evident for countries in Eastern Europe (Vlontzos et al. 2014). In reality, differences with respect to resources productivity between countries and/or agricultural regions are associated with different government support schemes for regions which are economically weaker and to the strengthening of specific regions where agriculture is still the central focus, as also assumed by Gorton and Davidova (2004).

It should also be noticed that the structure of agriculture in the EU varies not only from country to country but also between agricultural regions. As such, decisions on where and how to produce a specific agricultural crop or animal production should heavily depend over local conditions like the type of soil, climate, and infrastructures (Olsen 2010).

Conclusions

The results presented can play an important role in the agricultural context, given that estimates of technical efficiency by themselves provide specific and technical information to policy makers. For example, it is possible to know which countries

lead, in technical efficiency terms, at any moment in time. Provided the sample period considered, it also allows seeing which of these countries are using in the best sense the CAP.

The path of adjustment of agriculture of different countries in this period must be unequal. Some countries’ agricultural sectors were already allocating resources to the most competitive agricultural options, so they are expected to be more efficient with little change in technical efficiency patterns. Other countries have experienced with CAP different agricultural orientations than before. For these, we would expect, when learning curves are sufficiently overcome, and as CAP decoupling measures are introduced, to become more efficient than before. There seems to be a link between the less efficient countries and the countries that later joined the EU and the CAP which may explain this lack of learning curve.

In this article, we can also infer that resources productivity, domestic material consumption, and subsidies are very important factors explaining the estimated efficiency scores, either using DEA or SFA with GCE. The relevance of resource productivity to the technical efficiency of the sector shows that agricultural policy should encourage the rational and efficient use of resources, including also environmental criteria. The negative impact of organic crops on efficiency can show that given that these practices are still recent in many countries, it is necessary to allow time for a learning curve to be built, to improve efficiency in this type of crop. Finally, the importance of subsidies to animal production as a positive influence on efficiency, and the fact that these subsidies are coupled with production, can show the importance of turning to other types of subsidies coupled with production, namely subsidies to agricultural products (as these showed a negative influence on efficiency).

This article has the limitation of not considering all possible sources of influence over technical efficiency scores, as only a few number of available possible explanatory variables were used. As such, this work could be improved in the future by including more variables and by extending the analysis period to more recent years, which will only be possible as time goes by and data becomes available. Moreover, given the referred importance of regional aspects in Europe for the results of productivity and efficiency, it would be interesting to assess whether variables such as soil type, infrastructure, and climate are significant.

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Appendix

Table 3 DEA efficiency estimates for 27 European countries, by year

	2005	2006	2007	2008	2009	2010	2011	2012
Belgium	0.94	0.87	0.75	0.70	0.74	0.39	0.38	0.36
Bulgaria	0.46	0.41	0.20	0.32	0.36	0.33	0.30	0.27
Czech Republic	0.32	0.27	0.21	0.30	0.29	0.19	0.25	0.21
Denmark	0.97	0.94	0.85	0.95	1.00	0.83	0.98	0.87
Germany	0.62	0.63	0.60	0.74	0.60	0.45	0.35	0.32
Estonia	0.39	0.38	0.39	0.36	0.39	0.30	0.31	0.35
Ireland	0.52	0.33	0.30	0.30	0.25	0.21	0.21	0.19
Greece	0.90	0.84	0.83	0.80	0.85	0.83	0.78	0.76
Spain	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
France	1.00	1.00	0.95	1.00	0.93	0.87	0.92	0.82
Italy	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.96
Cyprus	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Latvia	0.30	0.28	0.27	0.30	0.33	0.23	0.20	0.25
Lithuania	0.33	0.33	0.30	0.33	0.33	0.24	0.30	0.43
Luxembourg	0.78	0.94	1.00	0.90	1.00	1.00	1.00	1.00
Hungary	0.29	0.28	0.18	0.31	0.24	0.19	0.23	0.18
Malta	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Netherlands	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Austria	0.57	0.57	0.55	0.62	0.53	0.49	0.59	0.50
Poland	0.24	0.24	0.24	0.25	0.25	0.24	0.23	0.25
Portugal	0.55	0.60	0.54	0.54	0.51	0.49	0.49	0.50
Romania	0.50	0.51	0.36	0.37	0.37	0.32	0.34	0.33
Slovenia	0.53	0.47	0.46	0.40	0.47	0.47	0.52	0.42
Slovakia	0.26	0.26	0.19	0.25	0.26	0.16	0.15	0.13
Finland	0.52	0.54	0.55	0.57	0.59	0.56	0.57	0.48
Sweden	0.49	0.53	0.51	0.52	0.45	0.41	0.46	0.47
United Kingdom	0.75	0.75	0.65	0.73	0.60	0.59	0.61	0.60

Table 4 SFA with GCE efficiency estimates for 27 European countries, by year

	2005	2006	2007	2008	2009	2010	2011	2012
Belgium	0.68	0.65	0.56	0.62	0.60	0.40	0.40	0.36
Bulgaria	0.69	0.62	0.39	0.55	0.57	0.47	0.42	0.39
Czech Republic	0.58	0.53	0.41	0.54	0.52	0.38	0.43	0.35
Denmark	0.68	0.68	0.61	0.69	0.72	0.66	0.70	0.68
Germany	0.61	0.60	0.54	0.65	0.63	0.52	0.44	0.44
Estonia	0.67	0.66	0.60	0.66	0.65	0.53	0.53	0.51
Ireland	0.71	0.61	0.53	0.58	0.52	0.44	0.42	0.36
Greece	0.74	0.72	0.68	0.72	0.72	0.66	0.64	0.64
Spain	0.92	0.94	0.97	0.96	0.96	0.97	0.96	0.95
France	0.79	0.79	0.76	0.78	0.79	0.78	0.78	0.77
Italy	0.73	0.78	0.76	0.79	0.78	0.72	0.69	0.70
Cyprus	0.88	0.88	0.91	0.89	0.89	0.91	0.90	0.90
Latvia	0.59	0.54	0.48	0.56	0.56	0.40	0.36	0.39
Lithuania	0.62	0.59	0.53	0.61	0.59	0.45	0.49	0.57
Luxembourg	0.68	0.76	0.76	0.76	0.82	0.83	0.78	0.82
Hungary	0.55	0.54	0.39	0.58	0.52	0.37	0.39	0.32
Malta	0.74	0.73	0.65	0.74	0.69	0.59	0.56	0.49
Netherlands	0.62	0.61	0.61	0.66	0.67	0.67	0.67	0.68
Austria	0.64	0.67	0.66	0.71	0.66	0.61	0.63	0.59
Poland	0.52	0.46	0.42	0.46	0.50	0.41	0.38	0.39
Portugal	0.67	0.73	0.67	0.70	0.68	0.60	0.57	0.57
Romania	0.64	0.68	0.57	0.59	0.61	0.48	0.47	0.45
Slovenia	0.57	0.58	0.53	0.55	0.57	0.47	0.45	0.40
Slovakia	0.55	0.52	0.39	0.50	0.50	0.32	0.28	0.24
Finland	0.59	0.62	0.58	0.64	0.65	0.62	0.61	0.55
Sweden	0.58	0.60	0.53	0.58	0.54	0.50	0.52	0.51
United Kingdom	0.73	0.72	0.64	0.70	0.63	0.64	0.65	0.64

Table 6. Results of fixed effects and quantile regression estimates (DEA method)

Independent variables	FE-VCE	Quantile regression				
		Q (0.10)	Q (0.25)	Q (0.50)	Q (0.75)	Q (0.90)
DMC (Biomass)	− 0.00***	− 0.00	− 0.00	− 0.00	0.00	0.00**
Resource productivity	− 0.028	0.03*	0.02*	0.02*	0.04*	0.08*
Crops products	0.00***	− 0.00***	− 0.00***	− 0.00	0.00	− 0.00
Organic crop area	− 0.011**	0.00***	0.00	− 0.00	− 0.00***	− 0.01*
Subsidies on product cereals	0.00	− 0.00	− 0.00	0.00	− 0.00***	− 0.00***
Subsidies on product animals	− 0.00	0.00***	0.00*	0.00*	0.00	0.00*
Pig population	− 0.00	0.00	0.00	0.00	0.00	0.00
Bovine population	0.00*	0.00	0.00***	0.00**	− 0.00	− 0.00**
Constant	0.32**	0.3167*	0.48*	0.58*	0.67*	0.82*
R^2 /pseudo R^2	0.23	0.19	0.22	0.20	0.21	0.33

Note: Dependent variable: scores of efficiency (based on the DEA model). FE-VCE stands for fixed effects with robust standard errors. *, **, *** means significant at 1, 5, and 10%, respectively. The number of observations refers to the total N in our sample = 216

Table 7. Specification and diagnosis tests

	Pooled	Random effects	Fixed Effects
Panel A: Model 1—DEA specification			
Modified Wald test (χ^2)			262.34***
Pesaran’s test		2.72***	1.89*
Frees’ test		1.18***	0.58**
Friedman’s test		17.32	14.70
Wooldridge test $F(N(0,1))$	14.20***		
Panel B: Model 2 SFA–GCE specification			
Modified Wald test (χ^2)			1023.29***
Pesaran’s test		13.68***	10.54***
Frees’ test		5.13***	3.75***
Friedman’s test		48.12***	41.58**
Wooldridge test $F(N(0,1))$	93.19***		

Note: Dependent variable: scores of efficiency (based on the DEA model and SFA-GCE methods). *, **, *** means significant at 1, 5, and 10%, respectively

Attending to the results of diagnosis tests presented in table A.5, we reject the null hypothesis of no cross-sectional dependence for the Agricultural sector in the panel of 27 countries of EU. This also happens when we assume two specifications of the two parametric and non-parametric models obtained through specifications DEA and SFA–GCE estimators. Besides, according to table A.5 results, we reject at the 1% level the null hypothesis of no first order autocorrelation for. A modified Wald statistics for group wise heteroscedasticity was used to analyze the existence of heteroscedasticity. Statistical evidence suggests the presence of contemporaneous correlation across all panel and, through both fixed and random effects model, at 1 and 5% significance level. This led us to the rejection of the null hypothesis of cross sectional independence according to Free’s Test and Pesaran’s Test, but not to reject the null hypothesis of cross sectional independence according to Friedman’s Test under method 1 of DEA, but to reject the null of cross sectional independence under SFA-GCE method 2 considering all test results

References

- Abay C, Miran B, Gunden C (2004) An analysis of input use efficiency in Tobacco production with respect to sustainability: the case study of Turkey. *J Sust Agr* 24(3):123–143
- Abdulai A, Huffman W (2000) Structural adjustment and economic efficiency of rice farmers in Northern Ghana. *Econ Develop Cult Change Univ Chicago Press* 48(3):503–520
- Akande, O.P. (2012) An evaluation of technical efficiency and agricultural productivity growth in EU regions. Wageningen University, <http://library.wur.nl/WebQuery/groenekenis/2002508>
- Arita S, Leung P (2014) A technical efficiency analysis of Hawaii's aquaculture industry. *J World Aquac Soc* 45:312–321
- Avadí A, Vázquez-Rowe I, Fréon P (2014) Eco-efficiency assessment of the Peruvian anchoveta steel and wooden fleets using the LCA-DEA framework. *J Clean Prod* 70:118–131
- Barnes AP, Revoredo-Giha C, Sauer J, Elliott J, Jones G (2010) A report on technical efficiency at the farm level 1989 to 2008. Report for Defra, London
- Bartolini F, Viaggi D (2013) The common agricultural policy and the determinants of changes in EU farm size. *Land Use Policy* 31: 126–135
- Baum, C.F. (2013) Quantile regression. <http://fmwww.bc.edu/EC-C/S2013/823/EC823.S2013.n04.slides.pdf>
- Bilgili F, Öztürk I, Koçak E, Bulut Ü, Pamuk Y, Muğaloğlu E, Bağlıtaş HH (2016) The influence of biomass energy consumption on CO2 emissions: a wavelet coherence approach. *Environ Sci Pollut Res* 23(19):19043–19061
- Bojnec Š, Fertő I, Jámbor A, Tóth J (2014) Determinants of technical efficiency in agriculture in new EU member states from Central and Eastern Europe. *Acta Oecon.* 64(2):197–217
- Bravo-Ureta BE, Evenson RE (1994) Efficiency in agricultural production: the case of peasant farmers in eastern Paraguay. *Agric. Econ.* 10(1):27–37
- Campbell R, Rogers K, Rezek J (2008) Efficient frontier estimation: a maximum entropy approach. *J Product Anal* 30(3):213–221
- Chen L, Jia G (2017) Environmental efficiency analysis of China's regional industry: a data envelopment analysis (DEA) based approach. *J Clean Prod* 142:846–853
- Chen Z, Huffman WE (2006) Measuring county-level technical efficiency of Chinese agriculture: a spatial analysis. In: Dong X-Y, Song S, Zhang X (eds) *China's agricultural development*. Ashgate Publishing Limited, Aldershot UK
- Coelli TJ, Prasada Rao DS, O'Donnell CJ, Battese GE (2005) *An Introduction to efficiency and productivity analysis*, 2nd edn. Springer, New York
- Coelli, T, Lauwers L, van Huynenbroeck G (2007). Environmental efficiency measurement and the materials balance condition. *Journal of Productivity Analysis*, 28:3–12.
- Färe R, Grosskopf S, Hernandez-Sancho F (2004) Environmental performance: an index number approach. *Res Energ Econ.* 26:343–352
- Farrell MJ (1957) The measurement of productive efficiency. *J Royal Stat Soc Series A* 120:253–290
- Fousekis P, Spathis P, Tsimboukas K (2001) Assessing the efficiency of sheep farming in mountainous areas of Greece: a non-parametric approach. *Agric Econ Rev* 2(2):5–15
- Garibaldi LA, Aizen MA, Klein A-M, Cunningham SA, Harder LH (2011) Global growth and stability of agricultural yield decrease with pollinator dependence. *Proc Natl Acad Sci USA* (14):5909–5914
- Giller KE, Rowe EC, de Ridder N, van Keulen H (2006) Resource use dynamics and interactions in the tropics: scaling up in space and time. *Agric Syst* 88:8–27
- Golan A, Judge G, Miller D (1996) *Maximum entropy econometrics: robust estimation with limited data*. John Wiley & Sons, Chichester
- Gorton M, Davidova S (2004) Farm productivity and efficiency in the CEE applicant countries: a synthesis of results. *J Agric Econ* 30:1–16
- Hoang VN, Alauddin M (2012) Input-orientated data envelopment analysis framework of measuring and decomposing economic, environmental and ecological efficiency: an application to OECD agriculture. *Environ Res Econ* 51:431–452
- Hoang VN, Coelli T (2011) Measurement of agricultural total factor productivity growth incorporating environmental factors: a nutrients balance approach. *J Environ Econ Manag* 62:462–474
- Hoang V-N, Rao DSP (2010) Measuring and decomposing sustainable efficiency in agricultural production: a cumulative exergy balance approach. *Ecol Econ* 69:1765–1776
- Hoang VN, Trung T (2013) Analysis of environmental efficiency variation: a materials balance approach. *Ecol Econ* 86(1):37–46
- Hoff A (2007) Second stage DEA: comparison of approaches for modelling the DEA score. *Europ J Operat Res* 181(1):425–435
- Ilyasu A, Mohamed ZA, Terano R (2016) Comparative analysis of technical efficiency for different production culture systems and species of freshwater aquaculture in Peninsular Malaysia. *Aquac Rep* 3:51–57
- Iraizoz B, Rapun M, Zabaleta I (2003) Assessing the technical efficiency of horticultural production in Navarra, Spain. *Agric Syst* 78:387–403
- Khoshnevisan B, Shariati HM, Rafiee S, Mousazadeh H (2014) Comparison of energy consumption and GHG emissions of open field and greenhouse strawberry production. *Renew Sust Energ Rev* 29:316–324
- Kočíšová K (2015) Application of the DEA on the measurement of efficiency in the EU countries. *Agric Econ* 61(2):51–62
- Koenker R, Bassett GS (1982) Robust tests for heteroscedasticity based on regression quantiles. *Economet.* 50:43–61
- Kumbhakar SC, Lovell CAK (2000) *Stochastic Frontier Analysis*. Cambridge Univ. Press, Cambridge
- Kwon OS, Lee H (2004) Productivity improvement in Korean rice farming: parametric and nonparametric analysis. *Aust J Agric Res Econ* 48(2):323–346
- Lauwers L (2009) Justifying the incorporation of the materials balance principle into frontier-based eco-efficiency models. *Ecol Econ* 68(6):1605–1614
- Li L, Hao T, Chi T (2017) Evaluation on China's forestry resources efficiency based on big data. *J Clean Prod* 142:513–523
- Macedo P, Scotto M (2014) Cross-entropy estimation in technical efficiency analysis. *J Math Econ* 54:124–130
- Macedo P, Silva E, Scotto M (2014) Technical efficiency with state-contingent production frontiers using maximum entropy estimators. *J Product Anal* 41(1):131–140
- McDonald J (2009) Using least squares and tobit in second stage DEA efficiency analyses. *Eur J Op Res* 197(2):792–798
- Minviel JJ, Latruffe L (2017) Effect of public subsidies on farm technical efficiency: a meta-analysis of empirical results. *Appl Econ* 49(2): 213–226
- Nguyen TT, Hoang VN, Seo B (2012) Cost and environmental efficiency of rice farms in South Korea. *Agric Econ* 43:367–376
- O'Garra T, Mourato S (2007) Public preferences for hydrogen buses: comparing interval data. OLS and quantile regression approaches. *Environ Res Econ* 36(4):389–411
- Olsen L (2010) Supporting a just transition: the role of international labour standards. *Int. J Lab Res* 2(2):293–318
- Picazo-Tadeo AJ, Beltrán-Esteve M, Gómez-Limón JA (2012) Assessing eco-efficiency with directional distance functions. *Europ J Operat Res* 220:798–809
- Qureshi MI, Awan U, Arshad Z, Rasli AM, Zaman K, Khan F (2016) Dynamic linkages among energy consumption, air pollution, greenhouse gas emissions and agricultural production in Pakistan: sustainable agriculture key to policy success. *Nat Haz* 84(1):367–363

- Reinhard S, Lovell CAK, Thijssen G (2002) Analysis of environmental efficiency variation. *Americ J Agric Econ* 84:1054–1065
- Reinhard S, Lovell KCA, Thijssen GJ (2000) Environmental efficiency with multiple environmentally detrimental variables; estimated with SFA and DEA. *Europ J Operat Res* 121:287–303
- Robaina-Alves M, Moutinho V (2014) Decomposition of energy-related GHG emissions in agriculture over 1995–2008 for European countries. *Appl Energy* 114:949–957
- Robaina-Alves M, Moutinho V, Macedo P (2015) A new frontier approach to model the eco-efficiency in European countries. *J Clean Prod* 103:562–573
- Schreurs, E., Peeters, L., Van Passel, S. (2014) Analyzing the impacts of soil contamination and urban development pressure on farmland values: Unconditional quantile regression estimation. 2014 International Congress, August 26-29 Ljubljana, Slovenia No. 182741, European Association of Agricultural Economists
- Sharma KR, Leung PS, Chen H, Peterson A (1999a) Economic efficiency and optimum stocking densities in fish polyculture: an application of data envelopment analysis (DEA) to Chinese fish farms. *Aquac.* 180:207–221
- Sharma KR, Leung PS, Zaleski HM (1999b) Technical, allocative and economic efficiencies in swine production in Hawaii: a comparison of parametric and nonparametric approaches. *J Agric Econ* 20:23–35
- Simar L, Wilson PW (2007) Estimation and inference in two-stage, semi-parametric models of production processes. *J Economet* 136:31–64
- Špicka, J. (2016) Changes in the energy efficiency of crop production in EU countries. *Proceedings of the 7th International Scientific Conference Rural Development 2015*:1-6.
- Toma E, Dobre C, Dona I, Cofas E (2015) DEA applicability in assessment of agriculture efficiency on areas with similar geographically patterns. *Agric Agric Sci Procedia* 6:704–711
- Toma P, Miglietta PP, Zurlini G, Valente D, Petrosillo I (2017) A non-parametric bootstrap-data envelopment analysis approach for environmental policy planning and management of agricultural efficiency in EU countries. *Ecol Ind* 83:132–143
- Van Meensel J, Lauwers L, Van Huylenbroeck G (2010) Communicative diagnosis of cost-saving options for reducing nitrogen emission from pig finishing. *J Environ Manag* 91(11):2370–2377
- Van Passel S, Van Huylenbroeck G, Lauwers L, Mathijs E (2009) Sustainable value assessment of farms using frontier efficiency benchmarks. *J Environ Manag* 90(10):3057–3069
- Vlontzos G, Niavis S, Manos B (2014) A DEA approach for estimating the agricultural energy and environmental efficiency of EU countries. *Renew Sust Energy Rev* 40:91–96
- Vlontzos G, Niavis S, Pardalos P (2017) Testing for environmental Kuznets curve in the EU agricultural sector through an Eco-(in)efficiency index. *Energies* 10(12):1–15
- Wasserstein RL, Lazar NA (2016) The ASA’s statement on p-values: context, process, and purpose. *Amer Stat* 70(2):129–133
- Xiao Y, Wu X-Z, Wang L, Liang J (2017) Optimal farmland conversion in China under double restraints of economic growth and resource protection. *J Clean Prod* 142:524–537
- Xu X, Jeffrey SR (1998) Efficiency and technical progress in traditional and modern agriculture: evidence from rice production in China. *Agric Econ* 18:157–165
- Zamanian GHR, Shahabinejad V, Yaghoubi M (2013) Application of DEA and SFA on the measurement of agricultural technical efficiency in MENA1 Countries. *Int J Appl Operat Res* 3:43–51
- Zelenyuk V, Zhaka V (2006) Corporate governance and Firm’s efficiency: the case of a transitional country, Ukraine. *J Product Anal* 25(1): 143–157
- Zhao C, Chen B (2014) Driving force analysis of the agricultural water footprint in China based on the LMDI method. *Environ Sci Technol* 48(21):12723–12731
- Zhou P, Ang BW, Poh KL (2006) Slacks-based efficiency measures for modelling environmental performance. *Ecol Econ* 60:111–118
- Zhou P, Poh KL, Ang BW (2007) A non-radial DEA approach to measuring environmental performance. *Eur J Operat Res* 178:1–9
- Zhu X, Demeter RM, Lansink AO (2012) Technical efficiency and productivity differentials of dairy farms in three EU countries: the role of CAP subsidies. *Agric Econ Rev* 13(1):66–92
- Zhu X, Lansink AO (2010) Impact of CAP subsidies on technical efficiency of crop farms in Germany, the Netherlands and Sweden. *J Agric Econ* 61(3):545–564
- Zhu Z, Wang K, Zhang B (2014) A network data envelopment analysis model to quantify the eco-efficiency of products: a case study of pesticides. *J Clean Prod* 69:67–73