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One- and multi-directional conditional efficiency measurement – Efficiency in Lithuanian family farms

Tomas Baležentis[a,*], Kristof De Witte[b,c]

[a] Vilnius University, Saulėtekio Ave. 9, LT-10222 Vilnius, Lithuania
[b] Katholieke Universiteit Leuven (KULeuven), Faculty of Business and Economics, Naamsestraat 69, 3000 Leuven, Belgium
[c] Maastricht University, TIER, Faculty of Economics and Business, Kapoenstraat 2, 6200 MD Maastricht, The Netherlands

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ABSTRACT

This paper analyses farming efficiency by the means of the partial frontiers and Multi-Directional Efficiency Analysis (MEA). In particular, we apply the idea of the conditional efficiency framework to the MEA approach to ensure that observations are compared to their homogeneous counterparts. Moreover, this paper shows that combining the traditional one-directional and multi-directional efficiency framework yields valuable insights. It allows one to identify what factors matter in terms of output production and input consumption. The application deals with Lithuanian family farms, for which we have a rich dataset. The results indicate that the output efficiency positively correlates to a time trend and negatively to the subsidy share in the total output. The MEA-based analysis further suggests that the time trend has been positively affecting the productive efficiency due to increase in the labour use efficiency. Meanwhile, the increasing subsidy rate has a negative influence upon MEA efficiencies associated with all the inputs.

1. Introduction

Since Farrell (1957) developed the idea of relative efficiency measurement, we can distinguish two broad approaches to measure efficiency. First, parametric methods do require the a priori specification of a representation[1] of the production technology, which is often unknown. Therefore, they can easily lead to specification errors (Yatchew, 1998). On the other hand, non-parametric methods do not require any assumptions on the functional form of the representations of the production technology. Data Envelopment Analysis (DEA; Charnes, Cooper, & Rhodes, 1978) can be given as a typical non-parametric frontier method. However, being a deterministic method in its nature, it does not account for random errors. Particularly this random variation is likely to occur in the context of farm efficiency analysis due to measurement errors, fluctuations related to operation environment, etc.

A partial frontier approach addresses these shortcomings. The partial frontiers (also referred to as the robust frontiers) are introduced by Cazals, Florens, and Simar (2002). The idea is to benchmark an observation not against all the observations dominating it but rather against a randomly drawn sample of these. The latter methodology has been extended by introducing the conditional measures enabling to analyse the influence of the environmental variables on the efficiency scores (Daraio & Simar, 2005, 2007a, 2007b).

The traditional Farrell's and Shepard's efficiency measures define a proportional contraction (resp. expansion) of inputs (resp. outputs). In many settings, including agriculture, the output-oriented direction is insightful as it reveals the output gap for given input levels. It can be used for benchmarking purposes as well as for policy insights in the potential improvements. Nevertheless, information on the potential input reductions or output expansions yields only partial insights due to three reasons. First, it considers proportional contractions or expansions.[2] In many settings, including agriculture, it is particularly interesting to obtain insights on the potential reduction of each input variable separately. The proportional contractions for all inputs hide too much information such that it is less useful for farmers and policy makers. Second, a decomposition of the (aggregate) efficiency scores into the input-specific efficiency scores would enable one to identify the sources of (in)efficiency, i.e. the inputs correlating to an overall decrease in productivity and efficiency. Third, for many observations it is not relevant to be benchmarked against any other observation

* Corresponding author at: Vilnius University, Saulėtekio Ave. 9, LT-10222 Vilnius, Lithuania. Tel.: +370 61241432.

E-mail addresses: tomas@laei.lt (T. Baležentis), Kristof.dewitte@kuleuven.be, k.dewitte@maastrichtuniversity.nl (K. De Witte).

[1] Primal representations of the production technology include production function and distance functions, among others. Dual representations of the production technology include the cost function, the profit function and the revenue function.

[2] However, it is possible to employ the subvector approach based upon the radial measures to obtain non-radial efficiencies (Färe et al., 1994). Indeed, we will follow this approach to a certain extent when employing the Multi-directional Efficiency Analysis.

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as external variation might influence the input–output ratio. Indeed, it is more relevant to be benchmarked against context-specific ideal points, which operate in a similar operational environment.

A technique which allows us to deal with those issues is Multi-directional Efficiency Analysis (MEA, Bogetoft & Hougaard, 1999). The latter methodology has been employed to analyse productive efficiency across various sectors, namely health care, banking, and energy (Asmild & Matthews, 2012; Asmild & Pastor, 2010; Wang, Wei, & Zhang, 2013).

In this paper we will combine the traditional measures to estimate relative efficiency with multi-directional efficiency. We show that this allows us to identify factors of efficiency along with the sources relaying the impact of these factors. This yields valuable and complementary insights for the evaluated observations, policy makers and researchers.

The economic crisis stressed the importance to look for efficiency gains in the agricultural sector. As it is the case in all Central and East European (CEE) countries, the agricultural sector constitutes an important part of the Lithuanian economy. Eurostat (2014) reports that the share of the gross domestic product (GDP) generated in the latter sector decreased from 4 per cent in 2004 down to 2.3 per cent in 2009; however it rebounded to 3.2 per cent in 2011 (in current prices). To compare, the respective figures for the 27 European Union (EU) Member States (EU27) are 1.8 per cent, 1.3 per cent, and 1.5 per cent. As for the “old” EU Member States (EU15), these figures are even lower, viz. 1.6 per cent, 1.2 per cent, and 1.3 per cent. The same pattern is revealed by considering the structure of employment: the share of employees working the agricultural sector is 15 per cent back in 2004, whereas it subsequently decreased to 8.3 per cent in 2008 and further down to 7.7 per cent in 2011. Meanwhile, the EU27 featured the shares of 5.8 per cent, 5 per cent, and 4.9 per cent, respectively. Considering the EU15, the corresponding figures are 3.2 per cent, 2.8 per cent, and 2.8 per cent. Thus, the Lithuanian agricultural sector still plays a relatively more important role in the Lithuanian economy as opposed to the economically advanced EU Member States. Even though the outcomes of the economic transition are evident, agriculture remains an economically and socially important activity in Lithuania.

In addition, the Lithuanian agricultural sector faces certain transformations due to the historical context prevailing in the CEE countries. Specifically, the collectivisation and de-collectivisation rendered distortions of the factor markets, which, in turn, have been shaping farmers’ decisions to a certain extent. Another important factor of the agricultural development in Lithuania is the European integration processes. Lithuania acceded to the EU in 2004 and thus adjusted its agricultural policy in the lines of the Common Agricultural Policy (CAP). As a result, the farm structure has been changing in terms of both land area and farming type. The aforementioned circumstances stress the need for researches into efficiency of the Lithuanian farms. In particular, these studies should identify the main reasons of inefficiency and possible paths for development. From an empirical perspective, this paper paves the road to do so.

This is not the first paper to analyse agricultural efficiency in CEE countries. Gorton and Davidova (2004) presented a survey of the relevant studies. Thiele and Brodersen (1999) used data envelopment analysis (DEA) to analyse the underlying differences in efficiency as regards East German and West German farms. Brümmer (2001) employed DEA and stochastic frontier analysis (SFA) to analyse the efficiency of Slovenian farms. Brümmer, Glauben, and Thijssen (2002) utilised SFA to analyse the changes in total factor productivity in dairy farms across Germany, Poland and the Netherlands. Bezlepkina and Oude Lansik (2006) utilised DEA in a two-stage framework to analyse the impact of financial indicators upon technical efficiency in Russian farms. Later on, Bojnec and Latruffe (2011, 2013) analysed the relationships between size and efficiency of Slovenian farms. Bojnec and Fertő (2013) employed SFA to analyse the relationships between efficiency and off-farm income. Latruffe, Balcombe, Davidova, and Zawalinska (2004, 2005) employed the bootstrapped DEA along with the SFA to estimate the efficiency of Polish farms. Balcombe, Davidova, and Latruffe (2008) analysed the determinants of the total factor productivity change in Polish farms. Davidova and Latruffe (2007) related the Czech farm efficiency to the financial indicators. Latruffe, Davidova, and Balcombe (2008) utilised the double bootstrapping methodology to assess the Czech farm efficiency. Chaplin, Davidova, and Gorton (2004) analysed the efficiency of Polish, Czech, and Hungarian farms. Latruffe, Fogarasi, and Desjeux (2012) compared the Hungarian and French farm performance by the means of DEA and meta-frontier approach. Baležentis and Kriščiukaitienė (2013) analysed the determinants of Lithuanian family farms’ efficiency by the means of the Tobit model, whereas Baležentis, Kriščiukaitienė, and Baležentis (2014) employed the bootstrapped DEA and the non-parametric regression for the latter purpose. Fousekis, Kourtesi, and Polymeros (2014) utilised the conditional framework to analyse the performance of Greek olive farms.

This paper exhibits certain noteworthy methodological and empirical features. From a methodological perspective it extends the MEA-model to include the operational environment. We do so by limiting the MEA reference observations to observations which have similar characteristics, as determined by a nonparametric multidimensional kernel specification. Second, this paper provides a framework to juxtapose the traditional one-directional efficiency estimations with multi-directional efficiency estimations. We show that a combination of the two approaches yields complimentary and valuable insights. Third, we examine the variables that correlate to agricultural efficiency in Lithuania. Given the economic crisis, the relatively high share of agriculture in GDP and call for efficiency gains within the European Common Agricultural Policy, insights in the drivers of efficiency are important for policy makers. The application makes use of rich farm-level data coming from the Farm Accountancy Data Network (Lithuanian Institute of Agrarian Economics, 2010).

This paper proceeds as follows. Section 2 presents the frontier methods, viz. order-m and MEA measures along with their conditional extensions. Section 3 presents the data used for benchmarking. The results are discussed in Section 4. The article concludes with policy advice and general remarks.

2. Single- and multi-directional conditional efficiency measurement

2.1. Single-directional efficiency measurement (order-m frontiers)

Ever since Koopmans (1951) and Debreu (1951) we define a production technology as the set of combinations of inputs, $x \in \mathbb{R}_+^p$, and outputs, $y \in \mathbb{R}_+^q$. The technology set, T, consists of all feasible combinations of inputs and outputs:

$$T = \{(x, y) \in \mathbb{R}_+^{p+q} \mid x \text{ can produce } y\}. \tag{1}$$

We assume that inputs and outputs are freely disposable (Shepard, 1970).

The input- and output-oriented Farrell measures of efficiency can be defined, respectively, as (Farrell, 1957):

$$\theta(x, y) = \min\{\theta \mid (\theta x, y) \in T\}, \tag{2}$$

$$\lambda(x, y) = \sup\{\lambda \mid (x, \lambda y) \in T\}. \tag{3}$$

In empirical studies, the ‘true’ set T and hence the efficiency scores are unknown. We only observe a random sample of the decision making units (DMUs), $\chi_K = \{(x_k, y_k) \mid k = 1, 2, \ldots, K\}$. For this sample of observations, one can estimate relative efficiency by using a non-parametric method (Charnes et al., 1978; Deprins, Simar, & Tulkens, 1984; Farrell, 1957).