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EFFICIENCY OF BIOMASS PRODUCTION – METHODOLOGICAL APPROACHES

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The article investigates methodological approaches towards economic efficiency, which may be applicable in case of biomass production with emphasis on agricultural biomass production – energy crops. The selected methods are: parametric stochastic frontier analysis (SFA) and non-parametric data envelopment analysis (DEA), which are suitable for efficiency measurement in agriculture. The study is organized in four sections. Introduction provides brief report on issues related to biomass production and term efficiency. Both methods (models) are shortly described in the material and methods chapter. In this part, bio-economy efficiency is shortly depicted as a modification of environmental efficiency. The results and discussion part explains limitations of models, inputs and outputs in terms of biomass production. The conclusion sums up the application of models. The results suggest the use of SFA on sector level and the use of DEA on farm level or regions basis.

Keywords: efficiency, biomass, inputs, outputs, production

Introduction

The importance of biomass as a source for production of renewable energy has been increasing in past few years. The EU has released regulations for biofuels and biomass, namely the EU Energy and Climate Change Package and Fuel Quality Directive which contains mandatory goals for 2020. One of the most important goals is 20 percent share for renewable energy in the EU total energy mix. In accordance with these regulations, the expectations of the European Commission are to reach heat and power production to account for nearly 45 percent of the renewable energy use in 2020 from solid biomass and about twelve percent from liquid biomass. As for the share of the primary energy production of renewable energy from the forestry, the sector of agriculture has grown more rapidly. Despite of this fact, forestry has the major contribution to renewable energy production from biomass.

The EU Energy and Climate Change Package also includes economic and social criteria. Economics of biomass production is rather a wide issue that may include modeling of biomass supply and demand for instance by Sharma, Ingalls, Jones and Khanchi (2013), a partial equilibrium model through OSCAR made by Sourie, Rozakis (2001), and various performance measurements. From the perspective of society, when technology interacts with the environment, it is essential that performance measurement considers the full impact of the production process (Antle et al., 2005; Weaver, 1996; Weaver et al., 1996).

In this article, the main focus is put on economic efficiency measurement methodology approaches, proposals and limitations. Economic efficiency is often illustrated by production frontier. The production frontier itself refers to state of technology in industry and shows the maximum output that can be achieved from given inputs. However, it is necessary to distinguish terms efficiency and productivity. The efficient decision making unit (DMU) operates on production frontier. Efficiency is therefore bounded to current state of technology. Productivity improvement is attained by either improving the state of technology or improving procedures. Thus productivity growth can be achieved by efficiency improvement. The productivity growth of biomass production is discussed in many other publications, for example Vance et al. (2014).

From early literature we can assume that economic efficiency consists of technical efficiency and allocative efficiency. Technical efficiency is related to the ability of the DMU to produce maximum output from given inputs or the minimum feasible amounts of inputs to produce a given level of output. The former definition is referred to as output-oriented TE, while the latter definition is referred to as input-oriented TE (Watkins, 2013). The allocative efficiency refers to the ability to use the set of inputs in optimal proportions, given their pertinent prices (Farrell, 1957). Economic efficiency is then calculated as the ratio of the minimum possible costs and the actual observed costs for a DMU and is the reflection of both efficiencies. One could argue that the relevant measure of efficiency of energy crop production can be simply the energy produced from a ton of biomass crop harvested for example. In fact, such indicators do not consider any other inputs used for production of that ton such as labour, costs for processing, fuels etc. The main problem of efficiency measurement is the clarification of all relevant inputs as it requires more than one factor of production.

The objective of our study was to outline some of the relevant methods for efficiency measurement possibly applicable in terms of biomass production. There are several methods generally applicable for economic efficiency measurement. We will further discuss parametric stochastic frontier analysis approach (SFA), non-parametric data envelopment analysis approach (DEA), and a relatively new type of efficiency measurement proposed by Zúniga (2012), known as bio-economy oriented efficiency.

Material and methods

Stochastic frontier production function – Cobb-Douglas form

This approach was developed as an adjustment of deterministic frontier estimators proposed by Aigner and Chu (1968), who used Cobb-Douglas production function in logarithmic form for n DMUs:

$$\ln y_i = F(x_i; \beta_i) - U_i \qquad (1)$$

$i - 1, 2, \ldots, n$

where:

y_i – features output of i-th DMU
x_i – stands for vector of input quantities used by DMU
β – the vector of unknown parameters to be estimated

U_i – represents non-negative variable indicating technical inefficiency in production

$F(.)$ – denotes appropriate function (Cobb-Douglas)

Aigner, Lovell and Schmidt (1977) created the estimation of a stochastic frontier production and added a symmetric error term to the non-negative error in (1) to provide:

$$\ln y_i = F(x_i; \beta_i) + V_i - U_i \tag{2}$$

$i = 1, 2, ..., n$

where:

V_i – is an indicator of random errors independent of the U_i.

The parameters of such defined model are assumed to be estimated by maximum likelihood (assumes normal distribution for V_i $N(0,\sigma_v^2)$, and half-normal or exponential distribution for U_i with mean u_i and variance σ_2. According to Mburu et al. (2014), variances of random errors σ_v^2 and those of technical and allocative inefficiency effects σ_u^2 might be expressed through the overall variance:

$$\sigma^2 = \sigma_v^2 + \sigma_u^2 \tag{3}$$

And thus technical (allocative) inefficiency can be expressed by the ratio $\gamma = \frac{\sigma_u^2}{\sigma^2}$.

Dual forms of technology

Coelli (1995) claims there are three main reasons for dual forms of production technology as cost or profit function; it is necessary to consider behavioral objectives as cost minimization; the need to account for multiple outputs; predict technical and allocative efficiency in the same time. Based on these implications, Mburu et al. (2014) further worked with equations above by subtracting v_i from (2):

$$\ln Y_i^* = y_i - v_i = F(x_i; \beta_i) - U_i \tag{4}$$

where:

Y_i^* – the observed output of i-th DMU adjusted by stochastic noise v_i. For this level of output, the technically efficient input vector for the i-th DMU X_i is constructed as a solution of (4) and the ratios $\frac{X_1}{X_i} = k_i$ (i >1) and k_i denotes the ratio of observed inputs. The dual cost frontier can be then derived and written in form:

$$\ln C_i = f(P_i; \alpha, Y_i^*; \alpha) \tag{5}$$

where:

C_i – represents minimum cost of observed level of output for i-th DMU

P_i – an input prices vector for i-th DMU

α – the vector of parameters to be estimated

The previous methodology assumes n DMUs observed in one point at time. When the data are observed in different time periods, it is vital to use panel data version of previous equations. This is a subject of a study conducted by authors Pitt and Lee (1981) or more recently Greene (2005).

Data envelopment analysis – efficiency measurement

DEA models attempt to measure efficiency involving multiple inputs and outputs. Cooper, Seiford and Zhu (2011) stress the relevance of DEA in case of unknown relationships between inputs and outputs. Podinovski, 2004 argues that in DEA models, the efficiency of the DMUs can be measured by solving mutually dual linear programming problems. One of them refers to the envelopment model and the other one to the multiplier model. These models can be constructed either as output oriented (maximization) or input oriented (minimization). They are also based on different return to scale assumptions. Seminal paper by Charnes et al. (1978) proposes original model CCR (Charnes Cooper Rhodes) built under the assumption of constant return to scale. Banker et al. (1984) made a modification of CCR model assuming variable returns to scale, known as BCC (Banker Charnes Cooper) model. Given the data on K inputs and M outputs for each of N DMUs, for the i-th DMU inputs and outputs are represented by vectors x_i and y_i. Then, we can assume that KXxN is the input matrix and MXxN is the output matrix, which represent data of all N DMUs. Coelli (1995) constructs DEA model purpose of which is to build a non-parametric envelopment frontier over the data point in a way that all observed points lie on or below the production frontier.

DEA in ratio form:

$$\max_{u,v}\left(\frac{u' y_i}{v' x_i}\right) \tag{6}$$

subject to: $\frac{u' y_j}{v' x_j} \leq 1, j = 1, 2, ..., N$

$u, v \geq 0$

where:

notation u is an MxI vector of output weights and v is a KxI vector of input weights. The problem of such formulation is infinite number of solutions. One possible solution is to impose constraint $vx_i = 1$ and thus create LP model:

$$\max_{\mu, v} (\mu' y_i) \tag{7}$$

subject to: $vx_i = 1$

$\mu' y_j - v' x_j \leq 0, j = 1, 2, ..., N$

$\mu, v \geq 0$

Change from u and v into μ and v illustrates the transformation and this form is called multiplier of the linear programming problem.

Envelopment form of this problem can be derived using the duality in linear programming:

$$\min_{\theta, \lambda} \theta \tag{8}$$

subject to: $-y_i + Y\lambda \geq 0$

$\theta x_i - X\lambda \geq 0$

$\lambda \geq 0$

where:

θ – a scalar indicating efficiency and λ is Nx1 vector of constants. The envelopment form is generally preferred because of fewer constraints. The value of θ stands for efficiency score of i-th DMU and will vary between 0 and 1. The value of 1 indicates technically efficient firm as a point on the production frontier according to Farell (1957). The linear programming problem must be solved N times for each DMU in the sample

Watkins (2013) specifies technical, allocative and economic efficiency of rice production for n farms through DEA model which might be apply for any kind of agricultural production, in form:

$$TE_n = \min_{\theta_i, \lambda n} \theta_n \tag{9}$$

subject to: $\sum_{i=1}^{I}\lambda_i x_{ij} - \Theta_n x_{nj} \le 0$

$$\sum_{i=1}^{I}\lambda_i y_{ik} - y_{nk} \ge 0$$

$$\sum_{i=1}^{I}\lambda_i = 1$$

$$\lambda_i \ge 0$$

where:

I – stands for farm
J – for input
K – for output
λ_i – non-negative weight for *i*-th farm
x_{ij} – an input *j* used by farm *i*
y_{ik} – an amount of output *k* produced by farm *i*

The economic efficiency score for *n* farm can be clarified by first solving the cost minimizing linear programming model:

$$MC_n = \min_{\lambda_i x^*_{nj}} \sum_{j=1}^{J} p_{nj} x^*_{nj} \tag{10}$$

subject to: $\sum_{i=1}^{I}\lambda_i x_{ij} - x^*_{nj} \le 0$

$$\sum_{i=1}^{I}\lambda_i y_{ik} - y_{nk} \ge 0$$

$$\sum_{i=1}^{I}\lambda_i = 1$$

$$\lambda_i \ge 0$$

where:

MC_n – minimal total cost for farm *n*
p_{nj} – is the price of input *j* for farm *n*
x^*_{nj} – the cost minimizing level of input *j* in farm *n* at given input price and level of output

Economic efficiency for each farm is then calculated as follows:

$$EE_n = \frac{\sum_{j=1}^{J} p_{nj} x^*_{nj}}{\sum_{j=1}^{J} p_{nj} x_{nj}} \tag{11}$$

where:

$\sum_{j=1}^{J} p_{nj} x_{nj}$ – the actual total cost observed for farm *n*

Unlike in general DEA formulation by Coelli (1995) presented by equations (7) and (8), Watkins (2013) works under variable returns to scale assumption. Variable returns to scale are expressed by constrain $\sum_{i=1}^{I}\lambda_i = 1$.

Bio-economic oriented efficiency

Bio-economic oriented efficiency (BE) is proposed by Zúniga (2012), whose study is based on Coelli´s et.al. (2007) environmental efficiency measure. The environmental efficiency incorporates material balance condition into production models. Material balance condition may be explained by the balance of nutrients and thus the difference between nutrients in inputs and nutrients in outputs. The pollution is reduced for example by reducing the nutrients content in input vector which causes reduction of nutrients balance. In this case, the materials contents of inputs are analogous to the input prices in a standard cost efficiency calculation, and hence parametric and non-parametric techniques are applicable in order to estimate the efficiency scores. Given a fixed output vector, Zúniga defines the environmental efficiency as the ratio of the smallest technically feasible bio economic balance over the observed bio economic balance and can be written in form:

$$BE = \frac{B_e}{B} = \frac{a' x_e}{a' x} \tag{12}$$

where:

$a'x_e$ – minimum nutrient content
$a'x$ – observed nutrient content

BE can be estimated by estimating cost efficiency in DEA models where the vector of nutrient contents of the inputs is used instead of prices. Hence it is possible to use previously described methods.

Results and discussion

The methods used for performance measurement may vary depending on the nature of research. In order to measure economic efficiency of biomass production it is vital to use more than one measure as each of the methodologies described previously is based on different assumptions.

SFA methodology

The main reason why SFA is a useful method for economic efficiency measurement of biomass production is its wide applicability in agriculture. The model of stochastic frontier estimation can be written in a form that supports behavioural objectives such as cost minimization (5). The cost minimization is the important assumption in dual frontier models. In our study we stated the example of Cobb-Douglas functional form of production function, which was commonly used in empirical estimations of frontier models. The logarithmic transformation enables a model to be linear in the logs of inputs and therefore applicable in econometric estimation.

The terms of inefficiency and random errors has appeared. Random errors are simply measurement errors which may occur but they are not taken into consideration in case of non-parametric methods. In case of inefficiency, the DMU is labelled inefficient when operating below the point on production frontier. The inefficiency and random error components are solved by making assumptions about their distributions. The random error term has usually normal distribution and the inefficiency term has usually a half-normal distribution. The parameters of the two distributions are estimated and can be used to estimate DMU´s specific inefficiency.

The estimation method used in stochastic frontier models is ML estimation, which estimates unknown parameters of models by setting the parameters´ values that maximize the likelihood function.

The SFA permits conducting of hypothesis testing in regard to the degree of inefficiency and productions structure.

The problem with SFA is that it does not account for multiple outputs and cannot measure technical and allocative efficiency in the same time. The main criticism of this method is based on distribution assumptions.

DEA methodology

DEA has become widely used in sector of agriculture just in the last decade. As discussed in the previous section, DEA models can be constructed either as output (maximization) or input (minimization) oriented. For output-oriented models, a DMU is not efficient when there is a possibility to enlarge output without increasing any input and without decreasing any other output. Moreover, in the input oriented models, a DMU is not efficient if it is possible to decrease any input without enlarging any other input and without decreasing any output. This methodology uses mathematic programming, in our case linear programming, and thus can deal with many variables. Furthermore, it is effectively applicable in case of multiple outputs.

In order to measure economic efficiency of biomass production, it is reasonable to construct the model under the assumption of variable return to scale, as we did in (9), (10) and (11), when measuring on multiple country bases, considering the fact that many industries are not perfectly competitive. Constant return to scale constrain is applicable under the assumption of constant size of DMUs.

DEA models are focused on measuring relative efficiency aspects of selected units. It is based on the variances of individual DMU compared to ideal DMU lying on the production frontier. The researchers can construct DEA in order to evaluate and interpret the efficiency from certain points of view and provide emphasis on many different subjects such as environment, sustainability, subsidies etc.

The problem of DEA is that it does not account for random errors or puts random error equals zero. On the other hand, the model is free to distribution assumptions.

When comparing DEA and SFA approach, it is necessary to stress that none of them is a superior method. Both methods have limitations as described earlier.

BE methodology

Bio-economy oriented efficiency is the methodology derived from environmental efficiency approach. Model of BE can be formed on basis of linear programming using the previously described methods. The main idea is to involve material balance condition into production model. Material balance condition explains content of nutrients in inputs. The description of BE in previous section is based on Zúniga´ approach that combines DEA approach with Malmquist total factor productivity methodology.

Data – outputs, inputs

In order to calculate economic efficiency of biomass there are different possibilities for data selection. Let us assume production of biomass crops such as corn, sugar beet, sunflower etc.

Outputs – the most commonly used output in case of agriculture is agricultural production in either monetary or physical units. The output is expressed by total amount of production in monetary units (relevant currency) or total revenue of the DMU. Physical units in terms of agricultural production are tons, or in case of biomass crop it could be renewable energy produced in ktoe (kilotonne of oil equivalent).

Inputs – decision about input set depends on topic of research related to biomass production. The most appropriate in this case appear to be initially labour, land and capital as any measurement of productivity. Labour in case of biomass crop production might be considered through number of workers in bioenergy sector or alternatively labour hours. Land is measured in hectares utilized for biomass-agricultural production. Capital factor can be considered in many ways of which we assume book value of machinery and inventory the most appropriate.

Costs are notably one of the most important input data. For biomass crops production it is vital to separate costs into input of seed, fertilizer, pesticides, energy consumption.

The last category of inputs is important in terms of environmental efficiency. Environmentally related inputs are for example nitrogen, phosphorus, potassium surplus. Input and output data may be found in corresponding database such as FADN (Farmers Accountancy Data Network).

Conclusion

The article dealt with the appropriate efficiency measurement in terms of biomass production. We can conclude that none of the proposed methodologies is superior and therefore it is desirable to use combination of BE with either SFA or DEA.

DEA seems to be more relevant in cases based on farm or region basis. It is also vital to use DEA in case of wider comparison. On the sectoral level, the use of SFA is considered more appropriate because of possible measurement errors and missing variables which might play an important role when it comes to efficiency. DEA requires a large number of observations to be relevant methodology of measurement. On the other hand, it does not require measurement unit's equivalence. Hence, we can conclude that the considered application has significant influence on the used methodology.

In the presented article we assumed energy crops production in regard to efficiency measurement. The biomass production is undoubtedly related to bioeconomy issues, thus we adduced the modification of environmental efficiency. The use of BE is adequate in respect of interaction between technology and environment which is certainly the case of biomass production.

Any of described methods can suffer from incorrectly selected or measured input data. Poorly measured inputs might have a significant impact over the technical efficiency measurement and influence the overall or economic efficiency. The crucial role of any conducted research on efficiency evaluation is selection of suitable data set.

Efficiency measurements of bioenergy sector is important from the point of fulfilling the goals set by the European Commission to increase the share of renewables in total energy mix and thus decrease the dependence on fossil fuels. There are many conflicting opinions on cultivation of agricultural crops as feedstock for energy purposes as it potentially reduces their nutritional aim. Despite criticism, biomass and waste from agriculture has become important sources in the field of bioenergy especially in the EU states.

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