Slovak University of Technology in Bratislava
Faculty of Mechanical Engineering
18th Conference on Applied Mathematics **APLIMAT 2019**

Proceedings

USING DEA TO ASSESS THE DIFFERENCES IN TECHNICAL EFFICIENCY BETWEEN FARMS MANAGED BY YOUNG AND OTHER FARMERS

ŠIMPACH Ondřej (CZ), ŠIMPACHOVÁ PECHROVÁ Marie (CZ)

Abstract. The aim of the paper is to assess the differences in technical efficiency between farms that are managed by young farmers (under 40 years) and other farmers using DEA. CCR and BCC input-oriented models are calculated and compared. Farms owned by young farmers are efficient from 54.2% and others from 51.6%. Average scale efficiency is also higher in case of young farmers. They have increasing returns to scale more often. The test reveals that the differences are statistically insignificant.

Keywords: data envelopment analysis, returns to scale, scale efficiency, technical efficiency

Mathematics Subject Classification: Primary 91G70; Secondary 62P20

1 Introduction

Generational renewal in agriculture is seen as crucial as young farmers are often seen as more effective and competent and are contributing more to the competitiveness of agriculture than other farmers. Davis et al. (2013) found out that "Younger farmers have longer planning horizon and tend to invest more heavily in business growth than comparable older age groups". "The aging farming population has a significant influence on production agriculture, succession planning, successors, and farmland usage." (Zou et al., 2018) We analyse and test whether the young farmers are more technically efficient than the others. We also examine pure and scale efficiency of the young farmers in comparison with others.

Concept of technical efficiency was defined by Farrell (1957) as the ability of a production unit to produce the maximum feasible output from a given set of inputs (input-oriented models) or to use minimum feasible inputs to produce a given level of output (output-oriented models). There are two approaches towards the estimation of the production function's frontier: stochastic modelling and linear (quadratic) programming. First, parametric, approach had been developed to Stochastic Frontier Analysis (SFA), second into non-parametric Data Envelopment Analysis (DEA). "DEA measures relative efficiency of a set of alternatives

(decision making units - DMUs) that consume multiple inputs and produce multiple outputs" (Jablonský, 2011).

The approaches are output-oriented or the input-oriented. To set the efficiency frontier of a production function, it is necessary to assume some type of returns to scale: decreasing, increasing, constant, non-increasing or non-decreasing. There are various types of models: CCR elaborated by Charnes, Cooper and Rhodes (1978), BCC by Banker, Charnes and Cooper (1989). There are also other types of models such as Free disposal hull, Free replicability hull, additive and super-efficiency models. We will focus on the first two models.

"In the traditional data envelopment analysis approach for a set of *n* Decision Making Units (DMUs), a standard DEA model is solved *n* times, one for each DMU." (Khezrimotlagh et al., in press). It allows to include more inputs *m* and outputs *r* into the transformation process, but the sum of them shall be at least three times lower than number of DMU ($n \geq 3(m+r)$).It is generally recommended to firstly select a small set of inputs and outputs at the beginning and gradually enlarging the set to observe the effects of the added items (Copper et al., 2007).

Regarding the determinants of technical efficiency in agriculture, it was found out by Bojnec et al. (2014) that it is "significantly positively associated with agricultural factor endowments, average farm size, farm specialisation, small-scale farms, and technological change. Foreign direct investments have an ambiguous effect". Similarly, Nowak et al. (2015) looked on the determinants of technical efficiency of farms in the EU and found out that important factors were: the soil quality, the age of the manager and the investments. On the other hand, the size of the farm was statistically insignificant. Also, Sağlam (2018) tried to find reasons of inefficiencies of wind farms in Texas by constructing a two-stage performance assessment. First, he used DEA to calculate the efficiency, then he elaborated the Tobit model for to investigate the reasons for inefficiency. The slack analysis and projection data of inefficient wind farms were used to find out optimal input-output variables.

Turčeková et al. (2015) employed DEA and output-oriented model with variable returns to scale to assess the environmental performance of EU 27 countries. They included also undesirable output. It was found out that Hungary, Luxembourg, Malta and Netherlands were efficient over the whole observed period 2008–2012. Environmental efficiency was also assessed by Reinhard et al. (2000) for Dutch dairy farms. They compared Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA) and revealed their strengths and weaknesses. Regarding DEA, its positive is that "can calculate environmental efficiency scores for all specifications, because regularity is imposed in this method" (Reinhard, Lovell and Thijssen, 2000).

2 Materials and Methods

The aim of the paper is to assess the differences in technical efficiency between farms that are managed by young farmers (under 40 years) and other farmers using Data Envelopment Analysis. Farms' accountancy data were obtained from database Albertina gathered by Bisnode s.r.o. company. The sample of farms was chosen to be as homogeneous as possible, i.e. companies with extreme values of the variables were excluded from the analysis. Young starting farmers were identified according to the list of recipients of the subsidy for setting-up

of young farmers' business from Common Agricultural Policy of the European Union. The sample consisted of farms that started their activity recently (2015 or 2016).

There were n = 58 decision making units with r = 2 outputs: y_1 – sales of own products and services, y_2 – sales of own goods and m = 4 inputs / production factors: x_1 – consumption of material and energy, x_2 – equity, x_3 – foreign sources, x_4 – number of employees. Description of the variables can be found in Table 1. Average sales were much higher in case of products as many companies did not sell goods at all. Average foreign sources were higher than own sources (equity). There were even negative own sources. In three cases the consumption of material was zero as certain companies of young farmers did not start to produce yet.

Variables	Mean	Median	Std. dev.	Min	Max
y_1	1489.43	492.50	1889.77	20.00	7468.00
y_2	37.91	0.00	147.37	0.00	982.00
x_1	566.86	19.50	1092.03	0.00	5434.00
x_2	1564.74	238.50	6626.72	-5495.00	46664.00
x_3	8405.28	2288.00	22913.09	7.00	169724.00
x_4	2.03	0.00	3.46	0.00	15.00

Tab. 1. Statistical decription of the sample. Source: own elaboration

Technical efficiency was calculated by Data Envelopment Analysis that enables to compare the decision-making units (farms) according to their performance. Thanks to DEA can be obtained the estimation of the efficiently of particular unit and the units can be sort according to it. It also provides the information which way shall be the behaviour of the unit improve in order to make it efficient. There is a production possibility set consisting of all possible combinations of inputs and outputs and the efficient units lie on the efficiency frontier (Jablonský and Dlouhý, 2004). As the outputs cannot be easily changed in agriculture (due to limited available land, more or less constant yields of crops and variable weather that influence the production), the input-oriented models were chosen. The aim is to minimize the inputs (i.e. the costs of production factors).

Two types of models were used to identify the frontier of the transformation function: CCR model proposed by Charnes et al. (1978) that assumes constant returns to scale and BCC model elaborated by Banker (1984) assuming variable returns to scale. Input oriented models that search how to improve input characteristics of the units, so the units become efficient were chosen. We selected two stage DEA. CCR model maximizes the efficiency level of unit U_q expressed as the ratio of weighted outputs and weighted inputs. under the condition that efficiencies of other units are equal or less than 1 (1).

$$\begin{aligned} \max \quad & z = \frac{\sum_i^r u_i y_{iq}}{\sum_j^m v_j x_{jq}} \\ \text{s. t.} \quad & z = \frac{\sum_i^r u_i y_{ik}}{\sum_j^m v_j x_{jk}} \le 1, \quad k = 1, 2, ..., n, \\ & u_i \ge \varepsilon, \quad i = 1, 2, ..., r, \\ & v_j \ge \varepsilon, \quad j = 1, 2, ..., m, \end{aligned} \tag{1}$$

where z is efficiency of unit U_q, x_{ik} is value of i-th input for unit U_k and y_{ik} is value of i-th output for unit U_k. There are m inputs, r outputs and n decision making units. v_i represents weights for inputs (i = 1, 2, ... m) and u_i are weights for outputs (i = 1, 2, ... r). ε is infinitesimal constant ensuring that all weights of inputs and outputs will be positive and included in a model. The value is usually set at 10^{-8}. This programming problem can be transformed to linear using Charnes-Cooper transformation setting the weighted sum of outputs to 1 as follows (2).

$$\begin{aligned} \max \quad & z = \sum_i^r u_i y_{iq} \\ \text{s. t.} \quad & \sum_i^r u_i y_{ik} \le \sum_j^m v_j x_{jk}, \quad k = 1, 2, ..., n, \\ & \sum_j^m v_j x_{jq} = 1 \\ & u_i \ge \varepsilon, \quad i = 1, 2, ..., r, \\ & v_j \ge \varepsilon, \quad j = 1, 2, ..., m, \end{aligned} \tag{2}$$

Assessed unit U_q lies at CCR efficiency frontier and is CCR efficient when $z^* = 1$. Unit with $z < 1$ is inefficient. For calculations and interpretation, a dual model is used (3).

$$\begin{aligned} \min \quad & \theta_q \\ \text{s. t.} \quad & \sum_j^n x_{ij} \lambda_j \le \theta_q x_{iq}, \quad i = 1, 2, ..., m, \\ & \sum_j^n y_{ij} \lambda_j \ge y_{iq}, \quad i = 1, 2, ..., r, \\ & \lambda_j \ge 0, \quad j = 1, 2, ..., n, \end{aligned} \tag{3}$$

where $\lambda = (\lambda_1, \lambda_2, ..., \lambda_n), \lambda_j \ge 0$ is a vector of weights of each unit. Another variable of a model is θ_q – a measure of efficiency of unit U_q. It can be interpreted as needed input reduction to achieving of efficiency frontier. When evaluating unit U_q, the model is searching for virtual unit characterized by inputs $\mathbf{X}\lambda$ and outputs $\mathbf{Y}\lambda$ that are linear combination of inputs and outputs of other units in dataset and that are not worse than inputs and outputs of the evaluated unit. For inputs and outputs of this virtual unit must be true that $\mathbf{X}\lambda \le \theta_q \mathbf{x}_q$ and $\mathbf{Y}\lambda \ge \mathbf{y}_q$. This situation is in case when efficiency $\theta_q = 1$ and all slack variables are zero. Adding the slack variables into the model, the calculation form of CCR input model will be in matrix form as (4).

$$\begin{aligned} \min \quad & z = \boldsymbol{\theta}_q - \boldsymbol{\varepsilon}(\mathbf{e}^{\mathbf{T}}\mathbf{s}^+ + \mathbf{e}^{\mathbf{T}}\mathbf{s}^-), \\ \text{s. t.} \quad & \mathbf{X}\lambda + \mathbf{s}^- = \boldsymbol{\theta}_q \mathbf{x}_q, \\ & \mathbf{Y}\lambda - \mathbf{s}^+ = \mathbf{y}_q, \\ & \lambda, \mathbf{s}^+, \mathbf{s}^- \ge 0, \end{aligned} \tag{4}$$

where $\mathbf{s}^+$ a $\mathbf{s}^-$ are vectors of slack variables for inputs and outputs, $\mathbf{e}^T = (1, 1, ..., 1)$. Evaluated unit U_q is efficient when optimal value of θ^*_q is one and optimal values of all slack variables are zero. Inefficient units have optimal value θ^*_q below one which shows proportional decrease of inputs to make U_q efficient. The difference between actual value of the input and output of particular inefficient unit and inputs $\mathbf{x}_q'$ and outputs $\mathbf{y}_q'$ that lies on efficiency frontier can be derived from the optimal results of the model either as (5) or (6).

$$\mathbf{x}'_q = \mathbf{X}\lambda^*, \quad \mathbf{y}'_q = \mathbf{Y}\lambda^*, \tag{5}$$

where $\boldsymbol{\lambda}^*$ is a vector of optimal weights calculated by model (3).

$$\mathbf{x}'_q = \boldsymbol{\theta}^*_q \mathbf{x}_q - \mathbf{s}^{*-}, \quad \mathbf{y}'_q = \mathbf{y}_q + \mathbf{s}^{*+}, \tag{6}$$

where symbols with asterisk * are vectors of optimal values of the model variables.

BCC model elaborated by Banker et al. (1989) assumes variable (decreasing, increasing or even also constant) returns to scale. Convex envelope cause that more units lie on the efficiency frontier. Previous CCR model is extended by the convexity condition $\mathbf{e}^{\mathrm{T}}\lambda = 1$. Primary BCC model is analogous to CCR.

$$\begin{aligned}
\max \quad & z = \sum_i^r u_i y_{iq} + \mu \\
\text{s. t.} \quad & \sum_i^r u_i y_{ik} + \mu \le \sum_j^m v_j x_{jk}, \quad k = 1, 2, ..., n, \\
& \sum_j^m v_j x_{jq} = 1 \\
& u_i \ge \varepsilon, \quad \acute{\imath} = 1, 2, ..., r, \\
& v_j \ge \varepsilon, \quad j = 1, 2, ..., m, \\
& \mu \quad - \quad \text{any}
\end{aligned} \tag{7}$$

where μ is dual variable assigned to the convexity condition of the model (8) which is dual BCC form of input-oriented model.

$$\begin{aligned}
\min \quad & z = \boldsymbol{\theta}_q - \boldsymbol{\varepsilon}(\mathbf{e}^{\mathbf{T}}\mathbf{s}^+ + \mathbf{e}^{\mathbf{T}}\mathbf{s}^-), \\
\text{s. t.} \quad & \mathbf{X}\lambda + \mathbf{s}^- = \boldsymbol{\theta}_q \mathbf{x}_q, \\
& \mathbf{Y}\lambda - \mathbf{s}^+ = \mathbf{y}_q, \\
& \mathbf{e}^{\mathbf{T}}\lambda = 1 \\
& \lambda, \mathbf{s}^+, \mathbf{s}^- \ge 0
\end{aligned} \tag{7}$$

Again, in case of 100% efficient unit the optimal value of $\boldsymbol{\theta}^*_q$ is equal to one and optimal values of all slack variables are zero, i.e. optimal value of objective function is $z^* = 1$. CCR and BCC models differ only in the values of variable μ (in CCR model is equal to zero, while in BCC can be any).

The differences in technical efficiency were tested using non-parametric Wilcoxon rank sum test as the distribution of the technical efficiency is not normal (it is skewed to the right). Calculations were done in econometric software Stata 15 using special command `dea` in a programme elaborated by Ji and Lee (2009).

3 Results and Discussion

Input oriented DEA two-stage model was elaborated and calculated. The results are displayed at Table 2. Average technical efficiency of the whole sample under constant RTS was 52.16% and under variable RTS 88.23%. As expected overall technical efficiency was lower than pure technical efficiency, where the frontier has concave form and more DMUs lie on the frontier. In case of constant returns to scale, there were 20 farms 100% efficient, but in case of variable RTS 45. Therefore, median is 1 in case of variable RTS and only 47.93% in case of constant RTS. There were 14 farms with decreasing, 27 with increasing and the rest with constant returns to scale. Scale technical efficiency that is the division of overall and pure technical efficiency was on average 60.71%.

Type of efficiency	Mean	Median	Std. dev.	Min.	Max.
Technical efficiency	0.5216	0.4793	0.4023	0.0046	1.0000
Pure technical efficiency	0.8823	1.0000	0.2855	0.0049	1.0000
Scale efficiency	0.6071	0.6481	0.3687	0.0205	1.0000

Tab. 2. Results of the input oriented DEA model; source: own elaboration

If we divide the sample on young and other farmers, we can see that young farmers are more overall technically efficient (from 54.20%) than the other (51.57%). Pure technical efficiency was also higher (93.77% in comparison with 86.65%). Scale efficiency was mildly higher (62.22% versus 60.28%). There were mostly farms with increasing returns to scale (44.44% in case of other farmers and 53.85% in case of young farmers). Then there were 13 and 4 farms with constant returns to scale, respetively. Comparison of the results for young and other farmers is displayed at Table 3.

Farmer	Others			Young		
Type of efficiency	Technical efficiency	Pure technical efficiency	Scale efficiency	Technical efficiency	Pure technical efficiency	Scale efficiency
Mean	0.5157	0.8665	0.6028	0.5420	0.9377	0.6222
Median	0.4439	1.0000	0.6589	0.5316	1.0000	0.6417
Std. dev.	0.4063	0.3028	0.3718	0.4037	0.2160	0.3734
Min.	0.0046	0.0049	0.0205	0.0747	0.2519	0.0975
Max.	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

Tab. 3. Results of the input oriented DEA model for young and other farmers; source: own elaboration

It was tested by Shapiro-Wilk test, whether the distribution of the technical efficiency is normal. From the mean and median it could be already suspected that the distribution is not normal and it was also confirmed by this test. Hence, the differences in technical efficiency were tested using non-parametric test. Non-parametric analogy of mann-Whitney test is two-sample Wilcoxon rank-sum test. However, all p-values showed that the average technical,

pure technical and scale efficiency do not differ between groups of young and other farmers. The p-values were 0.8118, 0.3868, and 0.9153, respetively.

Nevertheless, higher efficiency of young farmers can be assumed as it is proved by many researches. For example Nowak et al. (2015) found out that the age of the head is one of the important determinants of technical efficiency (calculated by DEA method) of farms in the EU. Also, Zaibet and Dharmapala (1999) expected that "younger people are more receptive to innovations and therefore a positive impact on productivity results". Their results, however, showed opposite result - young farmers were not more productive.

According to Latruffe et al. (2006) researchers Mathijs et al. (2000) who examined the production efficiency of Czech agriculture and Munroe (2001) who examined the efficency of Polish farmers "considered age as a proxy for farming experience and found a positive relation with technical efficiency in samples of Hungarian and Polish crop farms, but a negative effect in Bulgarian crop farms and Hungarian dairy farms."

Both types of relatively new farms in our sample are small, but farms of young farmers are smaller – they employ on average 1.15 employee, while the others 2.29. This factor also can play a role in efficiency. Expecially when also family (unpaid) labour is taken into account. For example in Brazil, one of the important determinants that influence the efficiency of agriculture in the regions is family labour. (see study of Barbosa et al., 2013). Monchuk et al. (2010) found out that counties in China with a large percentage of the rural labor force engaged in agriculture tend to be less efficient.

If we have a look on each DMU that is not efficient, we can find a peer unit with suggested value of the improvement – i.e. value how the inputs shall be reduce in order to increase the efficiency so the particular DMU becomes 100% efficient. We can also rank the firms according to the technical efficiency. There were 24 pure technically efficient firms which are on the first place, but the rest can be ranked on the other places. Those inefficient units shall improve their performance. We can describe as an example unit number 36. It is not a farm of a young farmer and is efficient only from 63.42%, exhibit decreasing RTS and is ranked on 46th position. It has three peer units – 39, 44, 46 that are all 100% efficient. In order to be efficient, unit number 36 shall reduce the input $x_{36,1}$ – consumption of material and energy from 3563.00 thous. CZK on 2808.69 thous. CZK. The equity ($x_{36,2}$) shall be reduced from 739.00 to -1693.64 thous. CZK – however this is not recommended to reduce own capital into the negative values (it is mathematical category and it is possible that it is negative). Also foreing sources shall be reduced from 16951.00 thous. CZK to 11299.01 thous. CZK, so the company shall not have that many debts. Finally the company should not employ 7 employees on permanent position, bur rather only 2 (1.74).

Input	**Empirical value of input *i* (thous. CZK)**				**Coefficient of reduction of input *i***			**Input *i***
i	$x_{36,i}$	$x_{39,i}$	$x_{44,i}$	$x_{46,i}$	$\lambda_{39,i}$	$\lambda_{44,i}$	$\lambda_{46,i}$	$x'_{36,i}$
1	3563.00	5434.00	3286.00	0.00	0.4186	0.1625	0.4189	2808.69
2	739.00	-5495.00	2946.00	305.00				-1693.64
3	16951.00	18223.00	6953.00	6066.00				11299.01
4	7.00	3.00	3.00	0.00				1.74

Tab. 4. Example of input reduction for unit number 36; source: own elaboration

Complete overview of inefficient units and their peers can be found in Table 5 in Appendix.

Despite that it seemed that young farmers are more technically efficient than the others, it cannot be clearly confirmed as the null hypothesis about equality could not have been rejected. However, the sample may have been too small – only 45 other farmers and 13 observations for young farmers (which also can be considered as too small sample for testing). Challenge for future research is to collect more and time-series type data.

4 Conclusion

The aim of the paper was to assess whether the young farmers are more technically efficient than the others. Non-parametric Data Envelopment Analysis was applied on a sample of farmers who started their business recently in order to compare similar firms. There were 13 farms of young and 45 of other age. Data were taken from Albertina database of accountancy data. The hypothesis was that farms of young farmers were more technically efficient than of other farmers, but the scale efficiency might be better in other farms as they might be larger and can achieve economy of scale. However, it could not be confirmed due to the lack of data for young farmers ($n < 30$). It is due to the fact that young farmers that are starting new farm are small and does not have to provide data in public register.

It was found out that average technical efficiency of young farmers was 54.20% and of others 51.57% under the constant returns to scale. Naturally, the pure technical efficiency was higher – young farmers were technically efficient from 93.77% and others from 86.68%. The differences in scale efficiency were not that high – young farmers were scale efficient from 62.26% and others from 60.28%. Despite that the sample was small, it was tested by non-parametric Wilcoxon rank-sum test, whether the farmers differ in technical efficiency. There were found none. However, results of other researches indicate that there can be differences.

Hence, challenge for the future is to collect data for more agricultural holdings and also in time series and to assess the technical efficiency by parametric Stochastic Frontier Analysis and test the differences also between years.

Acknowledgement

The paper was supported by grant from Internal Research Project of Institute of Agricultural Economics and Information no. 1113/2018 and from Czech Science Foundation Project no. P402/12/G097 “Dynamic Models in Economics”.

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Current address

Ondřej Šimpach, Ing., Ph.D.
University of Economics Prague, Faculty of Informatics and Statistics Winston Churchill sq. 4, 130 67 Prague 3, Czech Republic
E-mail: ondrej.simpach@vse.cz

Marie Šimpachová Pechrová, Ing., Ph.D.
Institute of Agricultural Economics and Information
Mánesova 75, 120 00 Prague 2, Czech Republic
E-mail: simpachova.marie@uzei.cz

Appendix

Unit no.	Rank	Eff.	Peer unit number							
			10	13	20	25	26	30	31	37
34	54	0.0049			0.9838	0.0049				0.0001
41	53	0.0160			0.9663	0.0123			0.0035	
21	52	0.0186	0.0005	0.1928	0.7875			0.0011	0.0182	
11	51	0.1704		0.5755	0.0303			0.1063	0.1704	
56	50	0.2519	0.0156	0.0663	0.7468				0.1550	
33	49	0.3150			0.3811		0.2167	0.0085	0.0677	0.3199
15	48	0.5994	0.1875				0.2128		0.0603	
35	47	0.6328	0.1832	0.1320					0.4496	
36	46	0.6342								
1	43	1.0000				0.2532			0.6701	
2	28	1.0000					0.5470			
3	34	1.0000					0.1826		0.8174	
4	37	1.0000		0.9373						
6	42	1.0000		0.1183	0.7748					
7	27	1.0000		0.3744	0.6256					
8	35	1.0000		1.0000						
12	33	1.0000		1.0000						
16	44	1.0000		1.0000						
17	31	1.0000		0.2825						
18	32	1.0000		0.4864				0.1335		
22	36	1.0000		0.2032						
23	29	1.0000		0.5952						
28	26	1.0000			0.9347			0.0653		
29	41	1.0000				0.2417				
43	45	1.0000		1.0000						
47	38	1.0000		1.0000						
48	39	1.0000			0.7482			0.2518		
51	40	1.0000				0.1690	0.1376		0.5079	
54	30	1.0000		0.2164	0.7739			0.0057		
58	25	1.0000		1.0000						

Tab 5a. Inefficient units with peer units and coefficients for reduction of inputs; zero values not displayed (value 1 is due to rounding despite that the units are not 100% efficient) ; source: own elaboration

Unit no.	Rank	Eff.	Peer unit number							
			39	40	44	45	46	50	52	57
34	54	0.0049	0.0068					0.0045		
41	53	0.0160	0.0179							
21	52	0.0186								
11	51	0.1704	0.1174							
56	50	0.2519				0.0163				
33	49	0.3150				0.0061				
15	48	0.5994		0.1914			0.3480			
35	47	0.6328	0.2323						0.0029	
36	46	0.6342	0.4186		0.1625		0.4189			
1	43	1.0000	0.0767							
2	28	1.0000								0.4530
3	34	1.0000								
4	37	1.0000	0.0627							
6	42	1.0000	0.1069							
7	27	1.0000								
8	35	1.0000								
12	33	1.0000								
16	44	1.0000								
17	31	1.0000	0.4323						0.2853	
18	32	1.0000	0.3801							
22	36	1.0000							0.7968	
23	29	1.0000								
28	26	1.0000								
29	41	1.0000								0.7583
43	45	1.0000								
47	38	1.0000								
48	39	1.0000								
51	40	1.0000								0.1855
54	30	1.0000								
58	25	1.0000								

Tab 5b. Inefficient units with peer units and coefficients for reduction of inputs; zero values not displayed (value 1 is due to rounding despite that the units are not 100% efficient) ; source: own elaboration