Efficiency of pork production in the Czech Republic and in an international context

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Abstract: The study presents the comparison of the performance and the ranking of pork producers in 16 countries in the period 2012 –2017. Data envelopment analysis (DEA) is used to make the ranking and identify the best practices among the involved countries ("peers"). For the DEA analysis, the output is aggregated into the category Carcass meat production in sow/year/kg, the inputs into Feed costs, Other variable costs, Labor costs, Depreciation and finance costs. In the first round of evaluation, only Brazil, the USA and the Netherlands were designated as peers. Significant differences between the highest-ranking values (1) and the lowest-ranking values (0.709) showed greater differences between European and non-European pork manufacturers. To get more European countries among the peers, non-European countries the USA and Brazil were excluded from the second round of evaluation. The second round of evaluation indicated that Belgium, the Czech Republic, Denmark, Finland, Italy, the Netherlands and Spain are efficient producers with regard to the given inputs. The ratings of Germany, Italy and France are close to one (with differences of less than 4%); therefore, these countries can also be classified as efficient units. The identification of peers among selected EU producers represents "best practices" in the field. In the study, "the best practice access" is used to show how the best performers achieve their excellent results. The greatest benefit of the benchmarking is not the measurement of DEA-excellence, but learning how best performance is achieved.

Key words: pork meat production, physical performance of pig production, Data envelopment analysis, ranking, peer, decision-making unit.

JEL classification: Q13, C22

1. INTRODUCTION

Pork is one of the mainstays of the Czech diet. Market prices of pork are currently on the rise both in the Czech Republic and throughout Europe. Since mid-March 2019, the prices of pigs processed at slaughterhouses have gone up by approximately a fifth, while individual, separately traded pig carcass parts have seen an increase of up to 40% in the Czech Republic. The rise in prices is due to both the higher proportion of meat being sold to China and the failure of meat processing plants to reduce the prices in the past when pigs were being marketed for less than the costs of processing them. As many farmers were forced to close down their production and lost all of their pigs as a result, the prices continue to go up (CNA, 2019). Between the turn of the millennium and March of 2019, the number of farmed pigs dropped from nearly 3.69 million down to 1.54 million, according to the Czech Statistical Office (2019). Another factor contributing to the mark up is the low self-sufficiency in pork production, which amounted to as little as 51.5% in the Czech Republic in 2018 (Ministry of Agriculture CR, 2018). It is, therefore, essential that the issue of pork production efficiency be considered from an international perspective. In our paper, we are proposing the DEA method.

The efficiency of pork production is also determined by the type of competition under which most companies within the industry operate. An oligopoly as the predominant type of imperfect competition in pork production may be described as a market structure characterized by a small number of firms within the industry and a relatively high degree of interdependence with respect to their decision-making. “These firms produce all, or at least most, of the output” (Frank and Cartwright, 2016).

“An oligopoly can exist when only a few firms (within an industry) are selling a given product, or when only a few companies are responsible for most (although not all) of the production” (Schiller, 2010). It usually involves large firms with a controlling share of the supply. The market concentration of pig slaughterhouses offers a good example of the pork production industry turning into an oligopoly. In 2008, the ten largest slaughterhouses in the Czech Republic slaughtered 44.65% of pigs, whereas in 2018, this figure rose up to 64%. In terms of numbers, this amounted to 1.63 million pigs in 2008 compared to the 1.49 million pigs slaughtered in 2018. Five of these slaughterhouses are operated by two corporate groups (AGROFERT, a.s., RABBIT Trhový Štěpánov, a.s.) and three family businesses based in Moravia. A comparison drawn between the performance and market share of Czech and German slaughterhouses shows that the slaughter market in Germany is even more oligopolistic. In 2018, ten of the largest slaughterhouses carried out nearly 80% of all pig slaughters (i.e. 78.9%); these ten companies slaughtered 44.74 million pigs in total. In 2018, 57.9% of pigs were slaughtered in the first three largest slaughterhouses, namely Tönnies (Rheda-Wiedenbrück), Vion (Düsseldorf) and Westfleisch (Münster). On top of that, the leading position of Tönnies, the largest slaughterhouse in Germany, experienced an additional boost between 2013 and 2018 as its market share had increased from 27.2% up to 29.3%, making it possible for the company to carry out the slaughter of 16.6 million pigs in 2018 (Maso.cz, 2019).

Companies in oligopolistic sectors of meat and meat product production are engaged in producing either homogeneous or heterogeneous products. With respect to homogeneous products (pigs for fattening), the competition reinforces the tendency towards a uniform balanced market price of pork due to the particularly strong interdependence of individual firms, whereby even the smallest price change initiated by one of them will considerably affect the behavior of the remaining firms. If meat processing plants produce differentiated products (dry salami, meat sausages, tripe sausages, etc.), the differences between the products of individual oligopolistic firms will not be as substantial in general; they are close substitutes.

The restrictions on (barriers against) new companies entering the sector of pork production include the relatively high capital costs of establishing a new firm, consumer preferences in relation to the existing firms, as well as the contracts and conventions (cartels) between the existing firms. If economies of scale present a barrier to entering this sector, then each firm seeking to do so should be achieving average costs of its products equally as low as those of the existing firms within the industry (Hořejší et al., 2018). A firm operating in two or more stages of production is said to have vertical economies of scope if the costs of jointly producing two or more vertically adjacent products is less than the costs of producing the products independently (Azzam, 1998). In this respect, the existence of an oligopoly is affected by the relationship between the market size and the optimum size of the given company (i.e. the size enabling this company to apply economies of scale).

"Sellers in an oligopoly will usually first consider the behavior of the other party before making a decision about their prices and/or outputs" (Frank and Cartwright, 2016). The firms mutually respond not only to price changes, but also to any changes in the output, in the product quality or the product advertising. The ability of each firm within the pork producing and/or pork processing industry to make reliable estimates of the competitors' reactions and actions hinges on the fact that only a few large firms operate in the sector, which gives the businesses a certain monopolistic advantage in that they can affect the volume of production by adjusting the price of pork or meat products. In addition, each firm is also able to control the entire market demand within the sector via its relatively higher share of the overall market supply of the goods. If a competitor is to respond to a change in the market price (market quantity), that change should essentially affect the change in its market price and market quantity.

The article follows previous research concerning the identification of best practices on the European pig market through the use of benchmarking. This was used to identify the critical success factors over which an organization has some control, in areas or processes for which this is necessary in order to achieve the best outcomes in the market. The results of previous studies (Baráth & Fertő, 2017) imply that total factor productivity has slightly decreased in the EU over the analysed period; however there are significant differences between the OMS and NMS and across Member States.

A univariate time series model was used to analyze the position of the Czech Republic among selected European pig producers in the period 2010 – 2018 (Smutka et al., 2018). The research proved that there are considerable differences among the producers. The aim of the research study is the comparison of the performance and the ranking of pork producers in 14 European countries, Brazil and the USA in the period 2012 – 2017. Performing manufacturers' assessments to identify the best practices leads to recommendations on the cost reduction and/or the changing of the production structure. The units that achieve the highest score in the benchmarking become the "benchmarks" or “peers” for others.

There are several ways to estimate the efficiency rates of producers involved in the evaluation. The most frequent are multicriteria decision-making methods and data envelopment analysis (DEA). The multicriteria decision-making methods suggest that the decision maker defines the weights of criteria, i.e. determines the significance of inputs and outputs in the model. Based on this, the model evaluates units and ranks them from best to worst. On the other hand, DEA models derive the weights of inputs and outputs using optimization procedures. Solving the models using linear programming methods, the units are divided into efficient and inefficient. If a unit is inefficient, the DEA model offers target values of inputs and outputs which lead to efficiency.

The DEA is a nonparametric technique used in the estimation of the efficiency of a homogeneous set of producers that are called Decision-Making Units (DMUs). DEA started out as a theoretical method in 1978, and it is widely applicable in developing and new areas today. The DEA models help to identify “efficient DMU” and to construct an efficient production frontier.

In this study, we follow previous methodology concerning the cost of pig meat and the productivity of the physical performance up to farm-gate level. DEA models are used for mutual benchmarking among the studied countries to answer the question of how to change inputs to improve the efficiency of pig meat production. Mutual comparison enables smaller units (regions, companies) to compare their own operations and achievements with the best available one, and thereby to design and implement their own strategy for improving their performance.

2. LITERATURE REVIEW

The DEA literature suggests several ways of dealing with applications in which the DMUs have different specializations or publication profiles.

Since the original DEA study (Charnes, Cooper and Rhodes, 1978), the implementation of the DEA models shows rapid and continuous growth in the field of applications of efficiency and productivity in both public and private sector activities. A comprehensive listing and analysis of DEA research covering the first 20 years of its history is not fully available. In 2002, Emrouznejad, Parker and Tavares (2008) identified 3,203 publications, and 6 years later, in 2008, inventoried more than 7,000 publications. This growth reflects not only the easier access to developing bibliography databases but also the need for user-friendly performance measurement methods. A listing of the most utilized/relevant journals, a keyword analysis, and selected statistics are presented, for example, in Chaowarat, Piboonrugnroj and Shi (2013), García-Alcaraz et al. (2015), Zhou et al. (2017).

DEA has been easily applicable due to the existence of study literature by Fulginiti (1998), Emrouznejad, Parker and Tavares (2008), and Zhu (2015), free software – Cooper, Seiford and Tone (2006) – and the teaching of DEA in graduate programs. Nowadays, it is quite usual for practitioners and decision-makers who are not professionals in operational research to run their own efficiency analyses.

According to a recent study by Liu et al. (2013), the largest areas of reported applications of DEA are banking, health care, transportation and education. Yang (2018) shows that last decade, around two-thirds of the DEA papers overall embed empirical data, while the remaining one-third are purely methodological. The application areas that have shown the highest growth momentum recently are energy, environment and agriculture.

The methodological problems of DEA applications are widely discussed in the papers. An article by Avkiran & Parker (2010) investigates the key dimensions underlying the progress realized by the DEA methodologies, borrowing from the social sciences literature. Emerging evidence of a declining number of influential methodological-based publications and a flattening diffusion of applications imply the unfolding maturity of the field.

Huguenin (2015) analyses the existing SW modules and argues that there are SW that are user-friendly and easily accessible to practitioners and decision-makers. This allows the possibility of providing evaluations using several alternative models including rather complicated environmental adjustments.

In agriculture, the problem of the specialization of farms is ubiquitous due to the large number of possible farm outputs, according to Davis (2017). In the same region, there are usually a variety of different crops and livestock products, each produced only by small farms and SMEs, while the big farms may produce only several common outputs. The stronger position of large companies on the market influences the prices of agricultural products. The bigger pig producers differ from standard farming producers because their production is highly specialized and similar to industry. Small farmers produce in a disadvantageous competitive environment and have to subsidize the realization prices of products from other sources. Antle et al. (2017) looked for the solution of the DMUs evaluation for farms where a large number of different crops may be produced in a particular region only, and few farms actually produce each particular crop. The authors illustrate the approach in which various outputs of production are related to one main output in different regions of Turkey. Kuo et al. (2014) discuss environmental conditions, which have to be put among other economic efficiency factors at the same time, and which enlarge the number of DEA factors. Thus, the DEA models should respect the people's request for both wildlife and environment conservation. Similar studies are presented by Picazo-Tadeo et al. (2011) and Coyne et al. (2015).

The DEA literature suggests several ways of dealing with applications in which DMUs have different specializations or publication profiles. DEA also operates in a stochastic environment. For example, Sharma et al. (1997) examine the productive efficiency of a sample of pig producers in Hawaii by estimating a stochastic frontier production function and the constant returns to scale (CRS) and variable returns to scale (VRS) output-oriented DEA models.

Other applications deal with fuzzy data; for example, Li et al. (2016), Mu et al. (2018).

Big data seems to have a broad range of applications in the future, for example in the market and financial areas – Kiani Mavi, Saen and Goh (2019).

Over the last two decades, two-stage DEA analysis (also two-stage DEA, two-stage network DEA structure) has been developed. Two-stage DEA models concern the internal structure of DMUs and measure their relative efficiency. Unlike conventional DEA models, where DMUs are "black boxes", two-stage DEA takes into account intermediate measures within each DMU. The results of two-stage DEA are thus more detailed than those obtained from the one-stage DEA approach, where the quality of inputs and outputs of DEA are ignored. The methodology of the input-oriented two-stage DEA model was elaborated by Färe and Whittaker (1995). Emrouznejad, Parker and Tavares (2008) provide a review of studies of two-stage DEA by examining the models, the structures of the network system and the methodologies used for the problem being studied. The study highlights directions for the future from the methodological and applicability point of view. Up to now, a couple of authors have presented two-stage DEA models. The works Liu et al. (2013) and Despotis, Sotiros and Koronakos (2016) explore new areas of application. Izadikhah and Saen (2018) present the two-stage DEA model for the evaluation of the sustainable supply chain as a key component of corporate responsibility in the presence of undesirable (and/or stochastic) data - Kiani Mavi, Saen and Goh (2019), Lim and Zhu (2019).

3. METHODOLOGY

3.1. Model description

Generally, two DEA types of models are used in the modelling process: input-oriented models and output-oriented models. An inefficient DMU can be made efficient by decreasing the inputs while the outputs remain constant (input orientation), or by increasing the outputs while keeping the inputs constant (output orientation).

The efficiency of DMUs is defined as a) technical efficiency and b) pure technical efficiency which are explained as follows:

1) Technical efficiency (TE) measures the performance of a DMU relative to other DMUs in a group and is expressed by the ratio of sum of the weighted outputs to the sum of the weighted inputs:

$$TE_j = \frac{u_1 y_{1j} + u_2 y_{2j} + \cdots + u_n y_{nj}}{v_1 x_{1j} + v_2 x_{2j} + \cdots + v_m x_{mj}} = \frac{\sum_{r=1}^{n} u_r y_{rj}}{\sum_{s=1}^{m} v_s x_{sj}} \quad (1)$$

where 'x' and 'y' denote input and output, and 'v' and 'u' represent input and output weights, respectively; 's' is the number of inputs, 'r' is the number of outputs and 'j' represents j-th DMU.

Charnes, Cooper and Rhodes (1978) translated Eq. (1) into linear programming model (2), where z is the technical efficiency representing i-th DMU.

$$z = \sum_{r=1}^{n} u_r y_{ri} = max$$

$$\sum_{s=1}^{m} v_s x_{sj} = 1$$

$$\sum_{r=1}^{n} u_r y_{ri} - \sum_{s=1}^{m} v_s x_{sj} \leq 0 \tag{2}$$

$$u_r \geq 0, \qquad v_s > 0, \qquad i = 1,2, \dots, k\,; j = 1,2, \dots, k$$

The evaluation of the DMU´s efficiency is calculated by means of the corresponding dual model. The relationships between the primary and dual models are evident in the matrix notation. The dual model corresponding to (2) can be stated as follows:

$$\begin{array}{cc} \text{Primary model} & \text{Dual model} \\ z = \boldsymbol{u}^T \boldsymbol{Y}_q & f = \theta - \varepsilon(\boldsymbol{e}^T \boldsymbol{s}^+ + \boldsymbol{e}^T \boldsymbol{s}^-) \\ \boldsymbol{v}^T \boldsymbol{X}_q = 1 & \boldsymbol{Y\lambda} - \boldsymbol{s}^+ = \boldsymbol{Y}_q \\ \boldsymbol{u^T Y} - \boldsymbol{v}^T \boldsymbol{X} \leq 0 & \boldsymbol{X\lambda} + \boldsymbol{s}^- = \theta \boldsymbol{X}_q \\ \boldsymbol{u} \geq 0, \quad \boldsymbol{v} \geq 0 & \boldsymbol{\lambda} \geq 0, \quad \boldsymbol{s}^+ \geq 0, \quad \boldsymbol{s}^- \geq 0 \end{array} \tag{3}$$

Where $\boldsymbol{\lambda} = (\lambda_1, \lambda_2, \dots, \lambda_n) \geq 0$ is the vector of weights assigned to each of the DMUs, $\boldsymbol{s}^+$ and $\boldsymbol{s}^-$ are slack variables balancing input and output of the DMUs. Variable θ measures the position among non-efficient DMUs and the production frontier originated by efficient DMUs. Vector $\boldsymbol{e}^T$ is the unit vector and ε is an infinitesimal constant.

Eqs. (3) are known as the ***CCR DEA*** model, in which we assume that the increase/decrease in inputs will result in a *proportional linear increase/decrease* in outputs. These models are also known as “*CRS DEA*”– constant return to scale models.

The CCR model has linear production frontier made of peer DMUs.

2) Banker, Charnes and Cooper (1984) developed another form of the DEA model, known as the ***BCC DEA*** model, called pure technical efficiency. It assumes that a change in inputs would result in a disproportionate change in outputs. These models are also known as “*VRS DEA*”– variable return to scale models.

Pure technical efficiency (PTE) assumes that a change in inputs would result in a *disproportionate change* in outputs: an increase or decrease. For this purpose, it is sufficient to extend the models (3) by the convexity condition $\boldsymbol{e}^T \lambda = 1$ as follows:

$$
\begin{aligned}
f &= \theta - \varepsilon(\boldsymbol{e}^T\boldsymbol{s}^+ + \boldsymbol{e}^T\boldsymbol{s}^-) \\
\boldsymbol{Y\lambda} - \boldsymbol{s}^+ &= \boldsymbol{Y}_q \\
\boldsymbol{X\lambda} + \boldsymbol{s}^- &= \theta\boldsymbol{X}_q \\
\boldsymbol{e}^T\boldsymbol{\lambda} &= 1 \\
\boldsymbol{\lambda} \geq 0, \quad \boldsymbol{s}^+ &\geq 0, \quad \boldsymbol{s}^- \geq 0
\end{aligned}
\tag{4}
$$

The BCC model has its production frontiers spanned by the convex hull originated by DMUs. The frontier has the linear and concave shape of a piecewise function.

The presented models and their modifications find the best set of weights for each input and output variable.

The dual solution of the Eqs. (3) and (4) radially contracts the input vectors ($\boldsymbol{X}$, $\boldsymbol{Y}$) to a projected point ($\boldsymbol{X\lambda}, \boldsymbol{Y\lambda}$) on the efficient frontier. Coefficients $\boldsymbol{\lambda} = (\lambda_1, \lambda_2, \dots, \lambda_n) \geq 0$ express the relative distance of the DMU from the efficient frontier originated by peers.

The DEA models measure the relative efficiency; that is, the efficiency of each DMU relative to the best DMUs in the sample (called "peer units"). Applying the DEA in evaluating the performance of a set of DMUs enables the formation of two clusters: DMUs that comprise an efficient frontier and inefficient DMUs lying below the frontier.

One of the main advantages of the DEA model is that it allows the incorporation of multiple inputs and outputs. It is clear from the conditions of this model that in BCC models a higher number of units will be marked as efficient.

If a DMU is fully efficient in both the technical and pure technical efficiency scores, it is operating at the most productive scale.

3.2. Model implementation

The research examines the analysis of the relative costs of pig meat production and of physical performance up to farm gate level. The sample size includes 16 countries in total: Austria, Belgium, Brazil, the Czech Republic, Denmark, Finland, France, Germany, Great Britain, Hungary, Ireland, Italy, the Netherlands, Spain, Sweden and the USA. In this article, DMUs refer to each of 16 selected countries.

The methodology follows the work of Avkiran and Parker (2010) investigating key dimensions underlying the progress realized by DEA methodologies. The formulas and computations in this study follow the publication by Brožová, Houška and Šubrt (2014).

The DEA modelling projects the inefficient DMUs onto the production frontiers implementing the CCR-projection and/or the BCC projection, among others. There are three directions implemented in the practice, according to Cooper & Seiford (2007):

1. The input oriented approach aims to reduce the input amounts as much as possible while keeping at least the present output levels.
2. The output oriented approach maximizes output levels under no more than the present input consumption.
3. Models that deal both with input excesses and output shortfalls simultaneously to try to maximize both jointly. If achievement of efficiency, or failure to do so, is the only topic of interest, then these different models will all yield the same result insofar as technical and mix inefficiency is concerned.

   This third approach is applied in this study.

The ranking evaluation will be carried out with average data from the period 2012 – 2017. DMUs with the same or very close ranking will be clustered into groups. The operation may reduce the number of DMUs.

The use of excellent European sources of data ensures that a farm structure in one nation is only compared to another nation with a similar structure. Pig production is characterized by multiple outputs and inputs. For the purpose of efficiency analysis, output is aggregated into one category: *Carcass meat production in sow/year/kg*. The inputs are aggregated into four categories, namely: *Feed costs, Other variable costs, Labor costs, Depreciation and finance costs.*

The choice between input and output orientation depends on the properties of the set of DMUs under study. Because there is only one output, while several inputs are used in this study, the input-oriented approach implementing BCC(I) and CCR(I) is assumed to be more appropriate for the task. Models BCC(O) and CCR(O) will finalize the overall evaluation.

3.3. Data search and elaboration

The data relating to the period 2012 – 2017 were collected mostly from the annual InterPIG reports (Davis, 2017). Missing data were extracted directly from national databases; see Table 1.

Table 1. Searching for relevant data in national databases.

Country	Data source	Country	Data source	Country	Data source
Brazil	Embrapa	Czech Republic	UZEI	Denmark	SEGES
France	IFIP	Great Britain	AHDB	Netherlands	LEI Wageningen
Ireland	Teagasc RER	Sweden	Svenska Pig	Hungary	Government

Source: AHDB PORK, 2012-17*; InterPIG 2012-17; IAEI 2012-2017; EUROSTAT 2012-17*

3.4. Input and output data for DEA models

Utilizing DEA we operate with 6-year data averages (2012 – 2017), which enable producers to be compared on the same scale. Descriptive statistics for all input and output variables and their averages are displayed in Table 2 and Table 3.

Table 2. Input and output data for selected DMUs for the period 2012 – 2017.

(I) Input (O) Output	Austria						Belgium					
	2012	2013	2014	2015	2016	2017	2012	2013	2014	2015	2016	2017
(I) Feed (EUR/kg)	1.122	1.095	0.980	0.923	0.904	0.867	1.171	2.130	1.042	0.978	0.916	0.913
(I) Other variable costs (EUR/kg)	0.259	0.282	0.273	0.248	0.244	0.251	0.210	0.224	0.199	0.193	0.208	0.217
(I) Labor (EUR/kg)	0.148	0.141	0.248	0.138	0.159	0.171	0.136	0.129	0.124	0.124	0.122	0.114
(I) Depreciation and finance (EUR/kg)	0.234	0.271	0.248	0.275	0.293	0.308	0.210	0.188	0.186	0.207	0.195	0.194
(O) Carcass production: 1 sow/year/kg	2,247	2,299	2,378	2,429	2,531	2,683	2,160	2,323	2,342	2,428	2,546	2,620

Czech Republic						Denmark						Finland					
2012	2013	2014	2015	2016	2017	2012	2013	2014	2015	2016	2017	2012	2013	2014	2015	2016	2017
1.245	1.071	0.956	1.177	1.192	1.208	1.060	1.060	1.060	1.060	1.060	1.060	1.011	1.059	0.993	0.840	0.806	0.787
0.321	0.483	0.472	0.484	0.474	0.464	0.247	0.247	0.247	0.247	0.247	0.247	0.259	0.271	0.240	0.358	0.379	0.377
0.197	0.141	0.112	0.151	0.150	0.148	0.148	0.148	0.148	0.148	0.148	0.148	0.148	0.141	0.137	0.179	0.183	0.171
0.136	0.141	0.137	0.124	0.116	0.107	0.197	0.197	0.197	0.197	0.197	0.197	0.185	0.188	0.199	0.289	0.317	0.319
2,145	2,143	2,185	2,187	2,243	2,245	2,088	2,086	2,167	2,172	2,157	2,234	2,356	2,289	2,287	2,230	2,296	2,326

France						Germany						Great Britain					
2012	2013	2014	2015	2016	2017	2012	2013	2014	2015	2016	2017	2012	2013	2014	2015	2016	2017
1.048	1.095	0.956	0.895	0.842	0.833	1.134	1.142	0.943	0.895	0.842	0.856	1.134	1.248	1.055	1.115	0.916	0.993
0.234	0.224	0.236	0.248	0.256	0.262	0.271	0.259	0.298	0.303	0.305	0.308	0.247	0.247	0.273	0.303	0.269	0.251
0.160	0.153	0.149	0.138	0.134	0.137	0.148	0.141	0.149	0.138	0.147	0.148	0.160	0.153	0.174	0.179	0.159	0.148
0.210	0.224	0.211	0.220	0.220	0.194	0.234	0.235	0.223	0.234	0.244	0.240	0.222	0.212	0.223	0.234	0.195	0.171
2,240	2,294	2,328	2,398	2,369	2,440	2,353	2,406	2,444	2,556	2,571	2,634	1,707	1,769	1,823	1,868	1,901	1,998

Hungary						Ireland						Italy					
2012	2013	2014	2015	2016	2017	2012	2013	2014	2015	2016	2017	2012	2013	2014	2015	2016	2017
1.048	0.953	1.018	1.088	1.013	0.913	1.208	1.330	1.179	1.115	1.026	1.015	1.344	1.377	1.328	1.239	1.209	1.209
0.332	0.294	0.285	0.317	0.244	0.262	0.222	0.235	0.261	0.262	0.256	0.262	0.222	0.224	0.248	0.220	0.244	0.251
0.148	0.153	0.161	0.165	0.122	0.137	0.136	0.129	0.124	0.138	0.134	0.137	0.160	0.153	0.174	0.165	0.171	0.171
0.222	0.247	0.230	0.248	0.220	0.205	0.197	0.200	0.186	0.207	0.195	0.228	0.234	0.247	0.199	0.220	0.220	0.251
1,989	2,109	2,107	2,010	2,116	2,103	1,943	2,030	2,061	2,058	2,195	2,285	2,842	2,900	2,942	3,128	3,132	3,126

The Netherlands						Spain						Sweden					
2012	2013	2014	2015	2016	2017	2012	2013	2014	2015	2016	2017	2012	2013	2014	2015	2016	2017
1.036	1.095	0.956	0.909	0.855	0.856	1.171	1.177	1.042	0.991	0.928	1.177	1.171	1.212	0.924	0.964	0.904	0.901
0.296	0.318	0.323	0.330	0.366	0.342	0.210	0.200	0.199	0.234	0.232	0.200	0.296	0.282	0.251	0.207	0.208	0.194
0.148	0.141	0.161	0.165	0.147	0.137	0.099	0.094	0.087	0.096	0.098	0.094	0.197	0.200	0.171	0.179	0.195	0.183
0.185	0.188	0.199	0.220	0.208	0.217	0.148	0.141	0.137	0.138	0.134	0.141	0.444	0.412	0.354	0.399	0.391	0.365
2,464	2,539	2,565	2,601	2,640	2,708	1,864	1,912	1,969	1,984	2,060	1,912	2,044	2,094	2,099	2,170	2,199	2,034

USA						Brazil						EU Average					
2012	2013	2014	2015	2016	2017	2012	2013	2014	2015	2016	2017	2012	2013	2014	2015	2016	2017
0.974	1.024	0.769	0.744	0.684	0.650	1.122	1.024	0.993	0.895	1.099	1.015	0.974	1.024	0.769	0.744	1.159	1.177
0.148	0.177	0.160	0.151	0.159	0.126	0.148	0.129	0.124	0.124	0.122	0.148	0.148	0.177	0.160	0.151	0.259	0.271
0.136	0.141	0.149	0.069	0.073	0.068	0.086	0.082	0.074	0.069	0.073	0.091	0.136	0.141	0.149	0.069	0.148	0.141
0.123	0.118	0.124	0.138	0.073	0.126	0.086	0.082	0.074	0.096	0.122	0.137	0.123	0.118	0.124	0.138	0.222	0.224
2,088	2,086	2,167	2,172	2,202	2,287	2,007	2,159	2,279	2,215	2,295	2,346	2,088	2,086	2,167	2,172	2,157	2,234

Source: Own data processing.

Table 3. Data for DEA ranking.

	(I) Feed	(I) Other variable costs	(I) Labor	(I) Depreciation and finance	(O) Carcass meat
Countries	Euro/kg/deadweights				Sow/year/kg
AUS	0.982	0.260	0.167	0.272	2,191
BEL	1.192	0.208	0.125	0.197	2,403
BRA	1.025	0.133	0.079	0.100	2,217
DEN	0.941	0.244	0.141	0.211	2,428
CR	1.141	0.449	0.150	0.127	2,068
FIN	0.916	0.314	0.160	0.250	2,297
FRA	0.945	0.243	0.145	0.213	2,345
GER	0.969	0.291	0.145	0.235	2,494
GB	1.077	0.265	0.162	0.210	1,844
HUN	1.006	0.289	0.148	0.229	2,072
IRE	1.146	0.250	0.133	0.202	2,095
ITA	1.284	0.235	0.166	0.229	2,586
NL	0.951	0.329	0.150	0.203	2,586
SPA	1.037	0.217	0.096	0.137	1,978
SWE	1.013	0.240	0.188	0.394	2,167
USA	0.808	0.153	0.106	0.117	2,167
EU	*1.031*	*0.266*	*0.147*	*0.225*	*2,447*

Source: InterPIG, 2012-17; EUROSTAT, 2012-17; IAEI, 2012-17. Own data processing.

The methodology of InterPIG was implemented in elaborating data with some national differences in definition, but where this has occurred the data has been adjusted in the most appropriate way. There is a wide variation in physical performance measures reported by countries, which can lead to a worsening in the marginal daily live weight gain and the marginal feed conversion ratio: (a) differences between countries in the weight of animals produced, (b) increase in slaughter weights, (c) length of time an animal is in the system.

The data were standardized on the basis of three weights: (a) transfer from breeding unit to rearing unit: 8kg (in GB = 7.1 kg), (b) transfer from rearing unit to finishing unit: 30kg (in GB = 37.1kg), (c) live weight at slaughter: 120kg (in GB = 105.4kg).

To ensure data consistency, all the financial data were converted into the EUR currency, using the fixed EUROSTAT exchange rates published for 2012 – 2017.

3.5. Data for DEA ranking procedure

Table 3 presents data, elaborated for the DEA ranking procedure. Average values, covering the period 2012 – 2017, summarize the financial performance: *Feed costs, Other variable costs, Labor costs, Depreciation and finance costs for inputs.* The data present the relative average costs of production within each country and make it possible to provide an accurate comparison within 0.80 – 1.5 €/kg of deadweight. The output represents *Carcass meat production sow/year/kg*.

3.6. Processing of data

DEA models were calculated using the program "DEA-Solver-LV 8.0" (http://www.saitech-inc.com/index.asp) including 28 clusters of DEA and enabling the solution of models of up to 50 DMU.

To check the consistency of DEA results with traditional unit ratings, models CCR and BCC will calculate the efficiency scores for each country. Countries with the same or very close ranking will be clustered into groups.

4. EMPIRICAL RESULTS AND DISCUSSION

4.1. First round of ranking

Efficiency scores, calculated for each individual country using CCR and BCC models, are presented in Table 4. The efficiency scores for input and output oriented CCR models are reciprocal values (Eq. 1). Thus, the CCR models in Table 4 give the same values.

Prerequisites of pure technical efficiency assume that a change in inputs would result in a disproportionate change in outputs. It means that in BCC trials, efficiency is equal to or higher than in CCR trials. Practical experience shows that BCC models give a higher number of peer units and are more selective. The same is true in our case.

Following the ideas presented in Paragraph 2.2., we start the evaluation of pig meat producers implementing both CCR and BCC models. The first round of the DEA procedure assigns peer positions to Brazil, the Netherlands and the USA; see Table 4.

Table 4. Data for DEA ranking.

DMUs	CCR(I)		CCR(O)	
	Rank	Score	Rank	Score
BRA	1	1	1	1
NL	1	1	1	1
USA	1	1	1	1
DEN	4	0.956	4	0.956
GER	5	0.950	5	0.950
FIN	6	0.922	6	0.922
FRA	7	0.920	7	0.920
BEL	8	0.831	8	0.831
AUS	9	0.827	9	0.827
SPA	10	0.826	10	0.826
SWE	11	0.794	11	0.794
CZECH	12	0.783	12	0.783
ITA	13	0.768	13	0.768
HUN	14	0.762	14	0.762
IRE	15	0.721	15	0.721
GB	16	0.635	16	0.635

DMUs	BCC(I)		BCC(O)	
	Rank	Score	Rank	Score
BRA	1	1	1	1
DEN	1	1	1	1
ITA	1	1	1	1
NL	1	1	1	1
USA	1	1	1	1
GER	6	0.973	6	0.991
BEL	7	0.963	7	0.988
FIN	8	0.930	8	0.965
FRA	9	0.926	9	0.925
SPA	10	0.919	10	0.894
CZECH	11	0.833	11	0.885
AUS	12	0.831	12	0.882
HUN	13	0.803	13	0.859
SWE	14	0.797	14	0.845
GB	15	0.750	15	0.816
IRE	16	0.750	16	0.728

Source: Own data processing.

Combining scores, the ranking procedure enables the categorization of countries into four domains: DEA-EXCELLENT, DEA-GOOD, DEA-AVERAGE, DEA-SUFFICIENT; see Table 5.

Table 5. Ranking of countries by CCR and BCC models on a < 0 – 1> scale.

RANK GROUPS	PEERS - EXCELLENT			GOOD				
	1			< 0,90 – 0,99 >				
DMUs	BRA	NL	USA	DEN	GER	FIN	FRA	BEL
Average	1	1	1	0.978	0.966	0.935	0.922	0.903
Rank	1	1	1	4	5	6	7	8
RANK GROUPS	AVERAGE					SUFFICIENT		
	< 0,80 – 0,90 >					< 0,70 – 0,79 >		
DMUs	AUS	SPA	SWE	CZECH	ITA	HUN	IRE	GB
Average	0.842	0.866	0.808	0.821	0.884	0.796	0.730	0.709
Rank	9	10	11	12	13	14	15	16

Source: Own data processing.

The ranking separates countries well and the ranking values are selective. Among the EU countries, Brazil and the USA, there are considerable differences between the highest and the lowest ranking scores.

Only one European country, the Netherlands, is assigned among the peer units (DEA excellent). Significant differences between the highest-ranking values (1) and the lowest-ranking values (0.709) show greater differences between the European and non-European pork manufacturers.

For mutual benchmarking, there is a need for more European countries among peer units. Therefore, we reduce the set of DMUs, excluding non-European countries the USA and Brazil from the evaluation.

4.2. Second round of ranking for reduced set of DMUs

The number of DMUs was reduced: Brazil and USA were excluded from the evaluation. CCR and BCC models were applied to evaluate the reduced set of DMUs involving 14 European pig meat producers. Efficiency scores calculated for each European country are included in Table 6.

When CCR and BCC trials are compared, the efficiency scores for the BCC trial are higher than those given by the CCR trial. The BCC model is less selective.

The results given in Table 6 indicate that the CCR trial offers 5 peers: BELGIUM, THE CZECH REPUBLIC, DENMARK, FINLAND and ITALY. The BCC trial expands peers to include THE NETHERLANDS and SPAIN.

Table 6. Data for DEA ranking – reduced set of DMUs.

CCR(I), CCR(O)			BCC(I)			BCC(O)		
DMUs	Rank	Score	DMUs	Rank	Score	DMUs	Rank	Score
BEL	1	1	BEL	1	1	BEL	1	1
CZECH	1	1	CZECH	1	1	CZECH	1	1
DEN	1	1	DEN	1	1	DEN	1	1
NL	1	1	FIN	1	1	FIN	1	1
SPA	1	1	ITA	1	1	ITA	1	1
GER	6	0.989	NL	1	1	NL	1	1
ITA	7	0.972	SPA	1	1	SPA	1	1
FRA	8	0.966	FRA	8	0.999	GER	8	0.990
FIN	9	0.924	GER	9	0.989	FRA	9	0.966
SWE	10	0.881	SWE	10	0.970	AUS	10	0.885
AUS	11	0.862	AUS	11	0.957	SWE	11	0.885
IRE	12	0.841	HUN	12	0.941	IRE	12	0.851
HUN	13	0.804	GB	13	0.901	HUN	13	0.817
GB	14	0.723	IRE	14	0.892	GB	14	0.733

Source: Own data processing.

Taking into account both the results of the CCR and BCC models, we can conclude that half of the studied EU countries are included among efficient producers with regard to the given inputs.

The top rated countries are the patterns for others; they become so-called “peers” in the DEA modelling terminology. The results of ranking can serve as a basis for future mutual benchmarking among the countries concerned.

Combining scores, the ranking procedure categorizes countries into four domains: DEA-EXCELLENT, DEA-GOOD, DEA-AVERAGE, DEA-SUFFICIENT; see Table 7.

The efficiency scores of studied countries assigned to the group GOOD are relatively high, which means that these countries did well in inputting production costs.

Table 7. Ranking of reduced set of countries by CCR and BCC models on a < 0 – 1 > scale.

RANK GROUPS	PEERS - EXCELLENT					GOOD	
	1					< 0.96 – 0.99 >	
DMUs	BEL	CZECH	DEN	NL	SPA	GER	ITA
Average	1	1	1	1	1	0.996	0.991
Rank	1	1	1	1	1	2	3
RANK GROUPS	GOOD		AVERAGE		SUFFICIENT		
	< 0.96 – 0.99 >		< 0.91 – 0.92 >		< 0.70 – 0.92 >		
DMUs	FRA	FIN	SWE	AUS	IRE	HUN	GB
Average	0.977	0.975	0.912	0.901	0.861	0.854	0.786
Rank	4	5	6	7	8	9	10

Source: Own data processing.

4.3. DEA excellent frontier and peers assignment

The DEA peer-processing assigns each *DEA-not-so-efficient* country a group of "peer countries", which serve as a benchmarking pattern for the realization of changes in the organization of inputs and outputs. As mentioned above, the choice between input and output orientation depends on the properties of the set of DMUs under study. Because there is only one output, while four inputs are used in this study, the input-oriented approach implementing BCC(I) and CCR(I) is assumed to be more appropriate for the task.

The efficient DMUs form an efficient frontier and become "peer units" for non-efficient DMUs.

A rate of less than one indicates the need for a proportional reduction of inputs for the DMU to become efficient. Each inefficient DMU has a set of efficient units, which create an efficient frontier which would act as a reference set to improve the performance of inefficient units. Coefficients $\lambda_1, \lambda_2, \dots, \lambda_n$ express the relative distance of a DMU from the efficient frontier originated by peers; see Table 6.

Table 8 presents the assignment of peers and coefficients „λ" to each of not-so-efficient countries.

Table 8. Assignment of peers along CCR and BCC input models.

CCR(I)	GOOD				AVERAGE		SUFFICIENT		
DMUs	GER (λ)	ITA (λ)	FRA (λ)	FIN (λ)	SWE (λ)	AUS (λ)	IRE (λ)	HUN (λ)	GB (λ)
Peers	DEN (0.425) NL (0.515) SPA (0.066)	BEL (0.946) DEN (0.129)	BEL (0.013) DEN (0.953)	DEN (0.038) NL 0.852)	BEL (0.199) DEN (0.695)	DEN (0.844) NL (0.055)	BEL (0.209) DEN (0.363) SPA (0.359)	DEN (0.437) NL (0.329) SPA (0.081)	DEN (0.535) NL (0.027) SPA (0.240)

BCC(I)	GOOD		AVERAGE		SUFFICIENT		
DMUs	GER (λ)	FRA (λ)	SWE (λ)	AUS (λ)	IRE (λ)	HUN (λ)	GB (λ)
Peers	BEL (0.031) DEN (0.392) NL (0.537) SPA (0.040)	DEN (0.974) SPA (0.026)	DEN (0.572) SPA (0.428)	DEN (0.934) FIN (0.066)	BEL (0.039) DEN (0.224) SPA (0.738)	DEN (0.952) SPA (0.048)	DEN (0.667) NL (0.033) SPA (0.299)

Source: Own data processing.

4.4. Projection of non-efficient DMUs onto DEA efficient frontier

Table 11 presents the projected input values of non-efficient DMUs on the efficient frontier originated by peers. The projection was computed separately for CCR(I) and BCC(I) models; see Table 6 and Table 8.

The CCR(I) model operates with the frontier consisting of 5 DEA-excellent DMUs: BELGIUM, THE CZECH REPUBLIC, DENMARK, THE NETHERLANDS and SPAIN; see Table 9.

Table 9. Participation on projection of selected countries - CCR(I) – peers.

CCR(I) – peers	BEL	CZECH	DEN	NL	SPA
Participation on projection	4x	0x	9x	5x	4x

Source: Own data processing.

The BCC(I) model operates with the frontier consisting of 7 DEA-excellent DMUs: BELGIUM, THE CZECH REPUBLIC, DENMARK, FINLAND, ITALY, THE NETHERLANDS and SPAIN; see Table 10.

Table 10. Participation on projection of selected countries - BCCR(I) – peers.

BCC(I) – peers	BEL	CZECH	DEN	FIN	ITA	NL	SPA
Participation on projection	2x	0x	7x	1x	0x	2x	6x

Source: Own data processing.

In both the CCR(I) and BCC(I) models, the most frequent roles of peers are played by DENMARK (16x), SPAIN (10x) and THE NETHERLANDS (5x). These countries will probably be able to offer best practice experience for the future benchmarking procedures. On the other hand, THE CZECH REPUBLIC (0x) and ITALY (0x), although they were ranked among peers, do not participate in the projection.

Other countries, being benchmarked with peers, should improve (i.e. lower) their production costs to reach the efficiency frontier. Coefficients "λ" indicate the required degree of approach to the assigned peer country (Table 8).

Computation of the new inputs is described in Brožová, Houška and Šubrt (2014).

We shall illustrate the procedure with examples: How to improve input costs to reach the DEA frontier and become a DEA-excellent country? For the calculation, we use the data in Table 3 and Table 8. Table 11 presents the complete results.

Table 11. Assignment of peers along CCR and BCC input models.

CCR(I)	Feed			Other variable costs			Labor			Depreciation		
DMU	Input	Change	%	Input	Change	%	Input	Change	%	Input	Change	%
GER	0.969	*0.958*	-1.1	0.291	*0.287*	-1.1	0.145	*0.143*	-1.1	0.235	*0.203*	-13.6
ITA	1.284	*1.249*	-2.8	0.235	*0.228*	-2.8	0.166	*0.136*	-17.7	0.229	*0.213*	-6.7
FRA	0.945	*0.912*	-3.4	0.243	*0.235*	-3.4	0.145	*0.136*	-6.2	0.213	*0.204*	-4.3
FIN	0.916	*0.847*	-7.6	0.314	*0.290*	-7.6	0.160	*0.133*	-16.7	0.250	*0.181*	-27.5
SWE	1.013	*0.892*	-11.9	0.240	*0.211*	-11.9	0.188	*0.123*	-34.4	0.394	*0.186*	-52.8
AUS	0.982	*0.847*	-13.8	0.260	*0.224*	-13.8	0.167	*0.127*	-24.0	0.272	*0.190*	-30.2
IRE	1.146	*0.964*	-15.9	0.250	*0.210*	-15.9	0.133	*0.112*	-15.9	0.202	*0.167*	-17.3
HUN	1.006	*0.808*	-19.6	0.289	*0.232*	-19.6	0.148	*0.119*	-19.6	0.229	*0.170*	-25.6
GB	1.077	*0.778*	-27.7	0.265	*0.191*	-27.7	0.162	*0.103*	-36.7	0.210	*0.152*	-27.7

BCC(I)	Feed			Other variable costs			Labor			Depreciation		
DMU	Input	Change	%	Input	Change	%	Input	Change	%	Input	Change	%
AUS	0.982	*0.939*	-4.3	0.260	*0.248*	-4.3	0.167	*0.142*	-15.0	0.272	*0.214*	-21.3
FRA	0.945	*0.944*	-0.1	0.243	*0.243*	-0.1	0.145	*0.140*	-3.6	0.213	*0.209*	-1.7
GER	0.969	*0.958*	-1.1	0.291	*0.288*	-1.1	0.145	*0.144*	-1.1	0.235	*0.203*	-13.6
GB	1.077	*0.970*	-9.9	0.265	*0.239*	-9.9	0.162	*0.128*	-21.1	0.210	*0.189*	-9.9
HUN	1.006	*0.946*	-5.9	0.289	*0.243*	-16.1	0.148	*0.139*	-5.9	0.229	*0.208*	-9.1
IRE	1.146	*1.022*	-10.8	0.250	*0.223*	-10.8	0.133	*0.107*	-19.4	0.202	*0.156*	-22.8
SWE	1.013	*0.982*	-3.0	0.240	*0.232*	-3.0	0.188	*0.122*	-35.0	0.394	*0.180*	-54.4

Source: Own data processing.

Example 1:

Let´s *implement the CCR model* for HUNGARY.

HUNGARY is ranked as a DEA non-sufficient producer. Three peers - DENMARK (0.437), THE NETHERLANDS (0.329) and SPAIN (0.359) - originate HUNGARY´s DEA frontier. To reach the frontier and become DEA-excellent, HUNGARY should *reduce Feed costs* from 1.006 € to the value 0.437*0.941 + 0.329*0.951 + 0.081*1.037 = 0.808 €, i.e. reduce Feed costs by 19.6%.

Similarly, *Other variable costs* - 0.289 € - that it has now, should be reduced to the value 0.437*0.243 + 0.329*1.329 + 0.081*0.217 = 0.232 €, i.e. Other variable costs should be reduced by 19.6%. For *Labor costs,* a similar calculation gives the value 0.119 €, e.g. reduced by 19.6%; for *Depreciation costs,* the value 0.170 €, i.e. reduced by 25.6%; see Table 11.

Example 2:

Let´s *implement the BCC model* for FRANCE.

FRANCE is ranked as a DEA non-sufficient producer. Two peers - DENMARK (0.974) and SPAIN (0.026) - originate FRANCE´s DEA frontier. To reach the frontier and become DEA-excellent, FRANCE should *reduce Feed costs* from 0.945 € to the value 0.974*0.941 + 0.026*1.037 = 0.944 €, i.e. reduce Feed costs by 0.13%.

Similarly, *Other variable costs* - 0.2434 € - that it has now, should be reduced to the value 0.974*0.2438 + 0.026*0.2171 = 0.2431 €, i.e. reduce Other variable costs by 0.12%. For *Labor costs,* a similar calculation gives the value 0.1399 €, i.e. Other variable costs should be reduced by 3.6%; for *Depreciation costs,* the value 0.2094 €, i.e. reduced by 1.7%; see Table 11. The changes that the French producers should make in general are minor, and in the preliminary stage of the benchmarking procedure, FRANCE also can be classified as an excellent producer.

Similar calculations for other non-sufficient countries are presented in Table 11.

5. CONCLUSION

In terms of pork production efficiency examined using the DEA method, the Czech Republic ranks among the best producers in Europe, along with Spain, the Netherlands, Germany and France. This is largely due to the results of the transformation process, which helped the Czech Republic draw on the invaluable experience of developed Western European economies in the field of pig farming. The concept of eco-efficiency is becoming increasingly popular as a tool to capture economic and environmental aspects of agricultural production. The literature to date has exclusively used the Data Envelopment Analysis (DEA) approach to measure producers' eco-efficiency (Orea & Wall, 2017). Great Britain is placed in the group of DEA-sufficient countries. If we take into account that Great Britain has a significant proportion of sows kept outdoors, the lower number of pigs weaned per sow per year seems to be a major cause of its relatively high costs of production compared with other EU countries. The stress to animals may cause its position in the ranking scale. Great Britain's result for litters per sow per year were £ 2.30 for indoor sows and £ 2.28 for outdoor sows in 2016. Considering also the soft criteria – animal welfare and the environment – Great Britain could be placed at the forefront of evaluation. As the preceding analysis demonstrates, pork production in developed economies is strongly oligopolistic. The reason lies in profits being generated from the scale of production, facilitating both the efficiency and profitability of production. The degree of oligopoly (78% of slaughters in Germany is carried out by only 10 slaughterhouses, while the 10 leading slaughterhouses in the Czech Republic currently perform 64% of all slaughters) may encourage the establishment of multinational cartels within the pork production sector, as can already be observed in several Western European countries.

Best practice and benchmarking are concepts which are quite easy to define in principle but very complex to operationalize. It is clear that “best practice” is a very relative notion, and all that can be done in reality is to seek examples of “good practice” or “good performance”, as those methods, processes and procedures used within an organization which lead to the successful achievement of its goals and the implementation of its policies, whatever they might be.

We have applied a multi-modelling approach using both CCR and BCC models simultaneously to try to maximize both jointly. These different input and output oriented models yield the results insofar as CRS DEA or VRS DEA are implemented and technical and mix inefficiency are concerned. Because there are 4 inputs and only 1 output used in this study, the input-oriented approach implementing BCC(I) and CCR(I) was stressed in the ranking procedure.

Only one European country, the Netherlands, was assigned among the peer units in the first round of evaluation. Significant differences between the highest-ranking values (1) and the lowest-ranking values (0.709) showed greater differences between the European and non-European pork manufacturers. To get more European countries among the peer units, non-European countries the USA and Brazil were excluded from the first step of the evaluation.

The second round of evaluation has classified about one-half of the studied EU countries as efficient producers with regard to the given inputs. Some other units have a rating very close to one, for example GERMANY and FRANCE, and these also can be classified as peers; see Table 7. The evaluation of ranking scores of non-efficient countries makes it possible to enlarge the set of excellent European producers.

In order to review efficient units and expand the set of non-efficient units, we can apply the so-called super DEA model. Unlike the CCR and BCC models, the supper DEA can also evaluate the efficiency rate of efficient units. The super DEA model returns ranking values that are greater than one. The higher the value, the more efficient the unit.

Table 12 shows the evaluation of units using the super DEA model. Both the CCR and the BCC models give the same results and the rating values correspond to the results obtained with the previous evaluation, Table 7. The rating of GERMANY, ITALY and FRANCE is very close to one: the differences are less than 4%. Therefore, these countries can also be classified as efficient units.

Table 12. Evaluation of producers using supper DEA ranking.

Supper DEA CCR(I) and Supper DEA BCC(I) ranking														
DMUs	SPA	CZE	BEL	NL	DEN	GER	ITA	FRA	FIN	SWE	AUS	IRE	HUN	GB
Rank	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Score	1.135	1.131	1.126	1.087	1.046	0.989	0.972	0.966	0.924	0.881	0.862	0.841	0.804	0.723
Frequency in reference Set	5x	1x	5x	4x	9x	-	-	-	-	-	-	-	-	-

Source: Own data processing.

DENMARK has the highest frequency relative to other DMUs in the reference set.

The identification of "peers" among selected EU producers presents "best practices" in the field. In the study, the "best practice access" is used to show how the best performers achieve their excellent results. "Best practice" is a very subjective concept and it is not possible directly to transfer the experience of one country fully to the unique situation and assumptions of another country. What is "best" for one country in one situation may not be "best" for another. That is why we have applied combinations of CCR(I), CCR(O) and BCC(I) and BCC(O) models to allow decision makers to make decisions based on local conditions.

The analysis of the presented ranking is considered as a "learning" process for both individuals and organizations. The users may use their criteria and techniques for their own evaluation of the presented data and ranking. The evaluation itself will never be perfect but, if professionally and critically carried out, it can provide immense benefits.

It must be noted that the DEA is not flawless. It does facilitate an estimate of the "relative" efficiency of a country within a group 14 countries, but it stops short of estimating absolute efficiency. It tells us how well a country performs within a given group based on chosen criteria. Another shortcoming is that the DEA models are based on extreme values and compare each unit to the best performers. This makes the DEA analysis more sensitive to data noise.

In this study, we have performed the first preliminary step in the identification of European countries for possible mutual benchmarking among pig meat producers. We have applied the "top-down" principle, starting the evaluation of high aggregated data on the national level covering the period 2014 – 2017. The next step will be the evaluation of the best producers and their best practices on the lower regional and company level. The methodology used for the lower regional level will be similar, properly managed for new but similar circumstances.

The greatest benefit of benchmarking is not the measurement of DEA-excellence, but the learning how best performance is achieved. A more detailed investigation in this field will be our future research.

ACKNOWLEDGEMENT

This research was supported by the grant *TA CR, PID: TL01000180*. The ÉTA programme supports research, experimental development and innovation of applied social sciences and humanities.

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