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An integrated data envelopment approach for evaluating the meat companies efficiency

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Abstract: The purpose of this study is to apply the assurance region (AR) concept to restrict the range of input-output weights with expert opinions in the data envelopment approach (DEA). Opinions from 34 experts were collected by a questionnaire in order to rank the importance of cost and revenue sources and measure the influence of business factors with the fuzzy analytic hierarchy process (FAHP). This article suggests that a DEA with AR specification in variable weights can present realistic results to measure and rank the performance of twenty meat auction companies (MAC) in Taiwan. We categorise MACs into four groups by decomposing their two revenue sources with auction and slaughter priority and recommend the managerial strategies for each group to improve operational efficiency. This consideration is more critical for small samples or industries that are close to the spatial competitive market structure.

Keywords: cluster analysis; efficiency decomposition; meat auction

The diagnosis and measurement of business performance is an essential management feature in the current pursuit of sustainable management. From the many analytical methods, data envelopment analysis (DEA) is one of the most commonly used for assessing the productivity of for-profit and non-profit organisations (Yu and Lin 2008; Fukuyama and Weber 2015; Amin and Hajjami 2016). The number of effective decision making units (DMUs) can be reviewed by measuring their relative efficiency values (Thompson et al. 1990; Thomas et al. 1998). However, the original DEA model, which is based on some input/output variables with coefficient at a value of 1 or 0, may override or ignore the importance for some minimal but influential factors, resulting in the possibility of faulty outcome and thus affecting the credibility of the model (Cook et al. 1991).

Many articles suggested that the weight-restricted concept can be used to enhance the estimation by limiting the range of the multipliers (or of the weights). The input/output variables within the assurance regions (AR) with experts' opinions can generate restricted multipliers for DEA model after considering the potential problem of overestimating the number of efficient DMUs (Lai et al. 2015).

Twenty wholesalers engage in wholesale auctions of pigs in Taiwan. Because of the convenient transportation and lack of long-term trade contract, pig farmers are free to decide whether to send pigs to the market in order to trade based on the auction price, and whether or not to use the slaughtering services provided. Therefore, the competition between Taiwan's pig auction markets is fierce, so performance research is fundamental. Market returns are mainly from auction and slaughter sources, and industry has always been controversial about which sources should be valued to improve their market performance.

Previous articles on analyzing the market efficiency by the DEA method did not focus on the importance of input projects and revenue sources for business performance. The conditions for too many DMUs qualified with high-performance index exist after evaluation. This result leads to a less powerful diagnosis (Thompson et al. 1990; Taylor et al. 1997; Liu and Chuang 2009).

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Therefore, this study considers the fuzzy analytic hierarchy process (FAHP) method, collecting experts' opinions on operating business projects for weighting the importance of sources for inputs and outputs in order to diagnose the market performance precisely. An integrated DEA method based on the AR concept relaxation is used to evaluate the operating performance of each meat auction company under the framework of spatial competition.

LITERATURE REVIEW

DEA-AR Model

DEA is a non-parametric mathematical programming approach for comparing the performances of related efficient DMUs from all observers by drawing an efficient output-versus-input frontier under the Pareto optimal conditions. The most significant feature of the estimating specification in the original DEA model is that it may allow the weights of all considered variables to be allocated. Some influential factors are included with the favorable weights to ensure the achievement of the most efficient state for the DMUs during estimation. After adding some specific over-weighted factors and waiving out those that are less efficient in allocation, this feature makes some DMUs to be qualified as an efficient unit with the efficiency index of 1 (Thompson et al. 1990; Cook et al. 1991; Lai et al. 2015). Thus, the analysis with indistinct weights may lead to an ambiguous diagnosis in measuring business practice for each DMU.

The augmented DEA model with AR specification is proposed to avoid the ambiguity of restricted efficiency index of 1 from the original DEA. We can gauge and limit the reliable range of weights for factors with expert opinions to improve the decision quality (Yu and Lin 2008; Liu and Chuang 2009).

The analytic hierarchy process (AHP) is a well-respected method of multiple-criteria decision-making (MCDM) approach, notably for pairwise comparisons between criteria and variables (Saaty 1980; Saaty 1987). Its primary concept was to use comparisons of paired factors to find the relative weight of each factor, primarily for uncertain situations and for issues with multiple evaluation criteria for decision-making. However, in AHP models, the value of pairwise comparison matrices cannot adequately take the uncertainty into account because of some problematic concerns, such as subjectivity and imprecision. While the model is popularly employed to capture experts' knowledge acquired through perceptions or preferences, AHP still cannot adequately reflect thoughts with its crisp numbers. In response to this development, the Fuzzy AHP model (Saaty 1987; Zadeh 1990; Saaty 2006) becomes a popular method in analyzing decision-making issues under uncertainty which can be applied in many topics with the advantage of reflecting the vagueness of human decision-making (Kuo et al. 2010; Kong and Fu 2012; Yu and Lee 2013).

Although the DEA model is widely used to evaluate the efficiency of a variety of business operations, research papers on the practice of meat market management are relatively few (Keramidou and Mimis 2011). Respecting the limited scope of an academic article, our paper proposes a practical industrial case by employing DEA-AR approach to analyze the performance by comparing the effectiveness of different outputs and the importance of input variables for meat auction companies with the expert view.

MODEL ELUCIDATION

DEA-AR Model

When DEA presumes that all DMUs operate under constant return to scale condition, inadequacy in DMUs operating scales may cause inefficient diagnostic results. Therefore, it is necessary to conduct the model of the variable return to scale. Accordingly, this study used the slack variable analysis in the BCC model (Banker et al. 1984) to improve the efficiency for DMUs by reallocating the input and output levels. The BCC application formula is as follows:

$$E_k = \mathrm{Max}\frac{\sum_{r=1}^{s} u_r Y_{rk} - u_0}{\sum_{i=1}^{m} v_i X_{ik}} \tag{1}$$

$$\text{subject to } \frac{\sum_{r=1}^{s} u_r Y_{rk} - u_0}{\sum_{i=1}^{m} v_i X_{ik}} \leq 1,$$

r (output) = 1, 2, ... , s; i (input) = 1, 2, ... , m; k (DMU) = 1, 2, ... , n; variable weights v_i, $v_r \geq \varepsilon > 0$, and u_0 is the intercept; E_k – technical efficiency of the k^{th} DMU; ε – a non-Archimedean small number, between 10^{-4}~10^{-6}.

Equation (1) converted into linear programming via the fixed denominator value to form the Equation (2):

$$\mathrm{Max}\ h_k = \sum_{r=1}^{s} u_r Y_{rk} - u_0 \tag{2}$$

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$$\text{subject to} \sum_{i=1}^{m} v_i X_{ik}$$

$$\sum_{r=1}^{s} u_r Y_{rj} - \sum_{i=1}^{m} v_i X_{ij} - u_0 \leq 0,\ j(DMU) = 1, 2, \ldots, n$$

Cook et al. (1991) point out that the variable weight selection processes in the traditional DEA model have some limits. The model selects the multipliers to maximize the objective value and may weight the multipliers at the relatively large or small number after calculation. The *prior* information of the weight values (u_2/u_1, v_2/v_1) for variables is obtained from expert opinions through questionnaires in Equations (3–4) (Taylor et al. 1997; Lai et al. 2015).

$$L_r \leq u_r/u_1 \leq U_r, \quad r \text{ (output)} = 2, \ldots, s \tag{3}$$

$$L_i \leq v_i/v_1 \leq U_i, \quad i \text{ (input)} = 2, \ldots, m \tag{4}$$

where L and U are the lower and uppper boundaries for variable weight, respectively; u_r/u_1 is the output weight ratio and v_i/v_1 is the input weight ratio.

EMPIRICAL ANALYSIS

Three steps are applied to elicit the upper- and lower-bounds of AR from expert opinion method with the FAHP (Aparicio et al. 2017; Kao 2017). First of all, the weight ranges of each significant variable are defined by analyzing the input and output components with the best practices (Table 1). Next, the performance efficiency of the meat auction companies is evaluated by using DEA-AR. Finally, cluster analysis on positioning MAC operation competitiveness in the industry is applied. The performance-evaluation model will be examined with the variable adjustments based on significance, and then categorized into groups with the efficiency decomposition approach, which provides a reference for further detailed evaluations.

Data are collected from the Taiwan area and cover the period of 2013–2015. Twenty registered meat auction market companies (DMUs) in Taiwan providing auction and slaughtering service are included. Figure 1 displays the locations of all companies.

Variable definition

Roll and Golany (1993) pointed out that too many inputs and outputs in the DEA application may result in an excessive number of efficient DMUs, which cannot be effectively segmented into different groups with levels. Thus, the Pearson correlation coefficient was calculated first in order to conduct a two-tailed test for the significance of the variable correlation. By a rule of thumb, this study selects seven input

Table 1. Definition of variables

Variable	Description
Number of employees (*NE*)	all full-time employees in a MAC (meat auction companies), including administration, auction/trade business, and electric slaughter services
Number of transactions (*NT*)	number of regular annual transactions in a MAC
Number of trading heads (*NA*)	total number of trading hog heads in the meat auction market for the whole year
Number of electric slaughter heads (*NS*)	total number of electric slaughter hogs in MAC in the whole year
Building area (*BA*)	building floor area, which contains the market space, parking space, mooring field, auction hall, offices, slaughterhouses
Personal expense (*PE*)	MAC requirements for full-time employment, labor costs such as employee salaries, employee benefits, and other administrative expenses
Operating expenses (*OE*)	item comprises usage fee, disposal fees, plus handling charges, taxes, operating expenses of electric slaughtering farm, supervision fees
Auction revenue (*UR*)	administration fees are 20 New Taiwan Dollars (NTD)* per 1 000 NTD traded and are shared equally between suppliers and traders
Slaughter revenue (*SR*)	income for slaughtering service for each hog

*the exchange rate for 1 EUR to NTD was around 35 in 2018

Source: Taiwan Area Meat Market Yearbook (2019)

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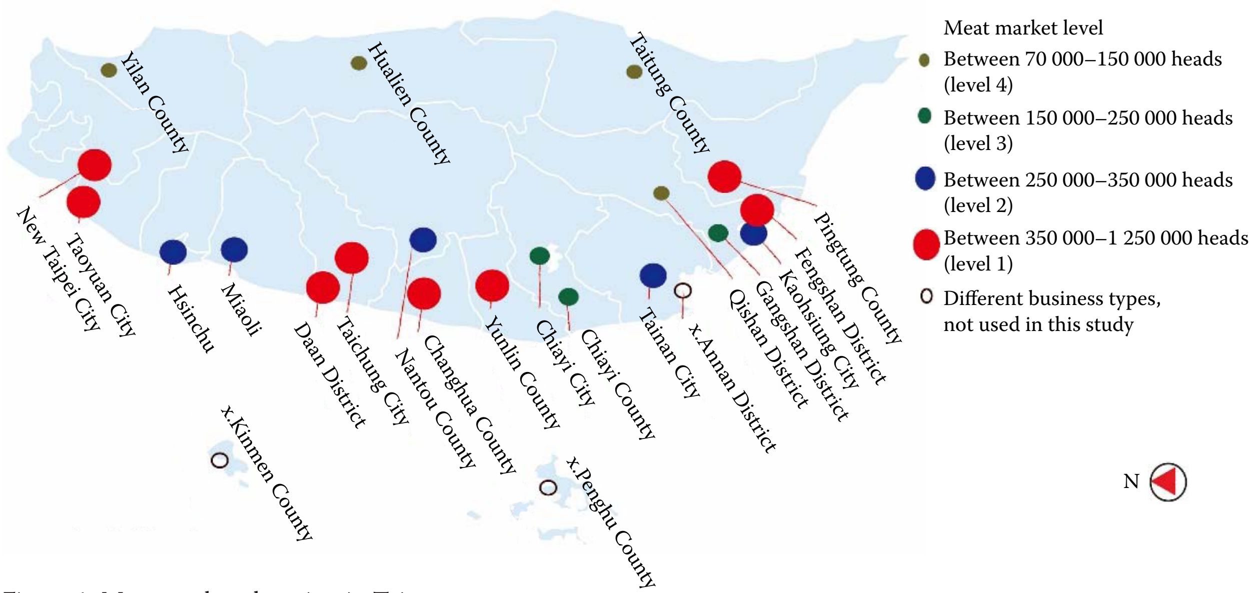

Figure 1. Meat markets location in Taiwan

Source: authors' elaboration

variables and two output variables after evaluating their statistics from 20 market units. Descriptive statistics and correlation coefficients of the variables are shown in Tables 2–3.

Table 2. Statistics on output/input data

Variables	Unit	Maximum	Minimum	Mean	Standard deviation
NE	person	96	14	53	24
NT	number	514	96	251	122
NA	number	833 614	58 021	344 044	219 313
NS	number	669 967	65 023	229 137	149 250
BA	m^2	19 152	4 312	9 586	4 308
PE	1 000 NTD	129 992	8 591	46 084	33 620
OE	1 000 NTD	76 977	8 073	37 049	21 065
UR	1 000 NTD	170 505	10 775	66 687	44 548
SR	1 000 NTD	73 588	5 255	27 408	20 471

NE – number of employees; *NT* – number of transactions; *NA* – number of trading heads; *NS* – number of electric slaughter heads; *BA* – building area; *PE* – personal expense; *OE* – operating expenses; *UR* – auction revenue; *SR* – slaughter revenue

Source: computed by this study

Table 3. Correlation coefficients between outputs and inputs

Revenue	Cost item						
	NE	*NT*	*NA*	*NS*	*BA*	*PE*	*OE*
UR	0.762**	0.586**	0.997**	0.875**	0.292	0.940**	0.869**
SR	0.900**	0.465*	0.699**	0.818**	0.573**	0.804**	0.795**

** and * represent correlation is significant at the 0.01 or 0.05 level, respectively; *NE* – number of employees; *NT* – number of transactions; *NA* – number of trading heads; *NS* – number of electric slaughter heads; *BA* – building area; *PE* – personal expense; *OE* – operating expenses; *UR* – auction revenue; *SR* – slaughter revenue

Source: computed by this study

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Table 4. FAHP weights of output and input for experts

Weight of variable	Expert No.																
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
W(*NE*)	0.025	0.026	0.031	0.024	0.016	0.081	0.024	0.026	0.020	0.017	0.019	0.034	0.084	0.053	0.042	0.076	0.041
W(*NT*)	0.374	0.389	0.265	0.462	0.425	0.043	0.046	0.076	0.068	0.049	0.241	0.204	0.068	0.099	0.030	0.247	0.136
W(*NA*)	0.234	0.232	0.265	0.260	0.254	0.023	0.361	0.223	0.423	0.179	0.241	0.401	0.257	0.337	0.458	0.189	0.136
W(*NS*)	0.068	0.075	0.086	0.089	0.127	0.014	0.336	0.086	0.281	0.195	0.193	0.139	0.248	0.212	0.141	0.132	0.229
W(*BA*)	0.061	0.066	0.092	0.087	0.087	0.149	0.016	0.376	0.048	0.283	0.034	0.045	0.103	0.12	0.246	0.107	0.099
W(*PE*)	0.099	0.098	0.105	0.047	0.054	0.268	0.109	0.062	0.102	0.048	0.228	0.089	0.120	0.134	0.052	0.188	0.065
W(*OE*)	0.139	0.115	0.156	0.031	0.038	0.422	0.109	0.150	0.059	0.230	0.044	0.089	0.120	0.043	0.033	0.061	0.293
W(*UR*)	0.874	0.874	0.874	0.874	0.874	0.895	0.500	0.874	0.895	0.831	0.500	0.895	0.500	0.500	0.895	0.895	0.888
W(*SR*)	0.126	0.126	0.126	0.126	0.126	0.105	0.500	0.126	0.105	0.170	0.500	0.105	0.500	0.500	0.105	0.105	0.112
Weight of variable	Expert No.																
	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34
W(*NE*)	0.038	0.043	0.042	0.043	0.085	0.094	0.062	0.220	0.223	0.031	0.020	0.024	0.028	0.017	0.038	0.031	0.075
W(*NT*)	0.275	0.217	0.215	0.217	0.078	0.171	0.261	0.154	0.156	0.265	0.170	0.164	0.242	0.124	0.163	0.195	0.281
W(*NA*)	0.267	0.409	0.415	0.409	0.304	0.307	0.194	0.174	0.131	0.265	0.331	0.354	0.240	0.374	0.330	0.211	0.075
W(*NS*)	0.148	0.195	0.193	0.195	0.065	0.123	0.202	0.085	0.116	0.086	0.179	0.127	0.087	0.264	0.047	0.102	0.203
W(*BA*)	0.019	0.019	0.019	0.019	0.174	0.050	0.057	0.085	0.065	0.092	0.115	0.106	0.229	0.082	0.115	0.018	0.248
W(*PE*)	0.042	0.078	0.078	0.078	0.248	0.183	0.052	0.134	0.160	0.105	0.095	0.101	0.112	0.082	0.163	0.283	0.036
W(*OE*)	0.212	0.038	0.038	0.038	0.046	0.074	0.173	0.148	0.150	0.156	0.091	0.125	0.063	0.058	0.145	0.160	0.083
W(*UR*)	0.895	0.888	0.888	0.888	0.874	0.874	0.739	0.874	0.895	0.500	0.500	0.500	0.874	0.500	0.500	0.895	0.500
W(*SR*)	0.105	0.112	0.112	0.112	0.126	0.126	0.261	0.126	0.105	0.500	0.500	0.500	0.126	0.500	0.500	0.105	0.500

W(.) – the weight of the output/input variable in parentheses; *NE* – number of employees; *NT* – number of transactions; *NA* – number of trading heads; *NS* – number of electric slaughter heads; *BA* – building area; *PE* – personal expense; *OE* – operating expenses; *UR* – auction revenue; *SR* – slaughter revenue; FAHP – fuzzy analytic hierarchy process

Source: computed by this study

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Table 5. FAHP results with expert opinions

Variable	Triangular fuzzy number	Weight	Normalized weight	Ranking
Input				
NE	(0.030, 0.048, 0.075)	0.064	0.047	7
NT	(0.116, 0.185, 0.302)	0.255	0.189	2
NA	(0.191, 0.308, 0.464)	0.395	0.292	1
NS	(0.096, 0.151, 0.245)	0.208	0.154	3
BA	(0.055, 0.087, 0.144)	0.122	0.090	6
PE	(0.073, 0.115, 0.189)	0.160	0.118	4
OE	(0.066, 0.106, 0.177)	0.149	0.110	5
Output				
UR	(0.454, 0.790, 1.351)	0.782	0.782	1
SR	(0.125, 0.210, 0.377)	0.218	0.218	2

NE – number of employees; *NT* – number of transactions; *NA* – number of trading heads; *NS* – number of electric slaughter heads; *BA* – building area; *PE* – personal expense; *OE* – operating expenses; *UR* – auction revenue; *SR* – slaughter revenue; FAHP – fuzzy analytic hierarchy process

Source: computed by this study

FAHP questionnaire analysis

Thirty-four completed questionnaires were collected out of the thirty-nine issued, providing us with a response rate of 87%. The average seniority of thirty-four interviewees was thirty years working experience with an average age of 58.

The FAHP results with variable weights from interviewing thirty-four experts are listed in Table 4 for each expert, and in Table 5 for each variable after calculation. Statistical results are consistent with the consensus assessment of the experts. The expert opinions stated that the most critical input variable in a MAC is the number of trading heads, with a weight value of 0.395, followed by the number of transactions, with a value of 0.255. For the two revenue sources, the experts said that earnings from the auction service are more critical than the revenues received from slaughter-related services, with weights of 0.782 and 0.218, respectively.

These findings also show that even though each MAC is equipped with massively-invested well-equipped slaughterhouses, which can provide the market with paid slaughtering services, the primary revenue source for most of these companies is still from auction services for live animals. For each variable, the maximum and minimum values from the interviewed experts were selected and divided by the difference between two values from both sides. We can define the weight ratios of these two ends after calculating the values for two sides (Table 6).

Table 6. Lower and upper bounds for the FAHP/DEA-AR model

Weight ratio	Lower	Upper
W(*NE*)/W(*NT*)	0.482	0.521
W(*NE*)/W(*NA*)	0.487	0.672
W(*NE*)/W(*NS*)	0.662	1.073
W(*NE*)/W(*BA*)	0.592	0.998
W(*NE*)/W(*PE*)	0.434	0.786
W(*NE*)/W(*OE*)	0.493	0.528
W(*NT*)/W(*NA*)	1.010	1.290
W(*NT*)/W(*NS*)	1.375	2.060
W(*NT*)/W(*BA*)	1.228	1.917
W(*NT*)/W(*PE*)	0.834	1.632
W(*NT*)/W(*OE*)	0.947	1.095
W(*NA*)/W(*NS*)	1.361	1.597
W(*NA*)/W(*BA*)	1.216	1.486
W(*NA*)/W(*PE*)	0.646	1.615
W(*NA*)/W(*OE*)	0.735	1.084
W(*NS*)/W(*BA*)	0.893	0.931
W(*NS*)/W(*PE*)	0.405	1.187
W(*NS*)/W(*OE*)	0.460	0.797
W(*BA*)W(*PE*)	0.435	1.328
W(*BA*)/W(*OE*)	0.494	0.892
W(*PE*)/W(*OE*)	0.671	1.137
UR/*SR*	1.118	1.897

W(.) – the weight of the output/input variable in parentheses; *NE* – number of employees; *NT* – number of transactions; *NA* – number of trading heads; *NS* – number of electric slaughter heads; *BA* – building area; *PE* – personal expense; *OE* – operating expenses; *UR* – auction revenue; *SR* – slaughter revenue; FAHP/DEA-AR model – integrated model

Source: computed by this study

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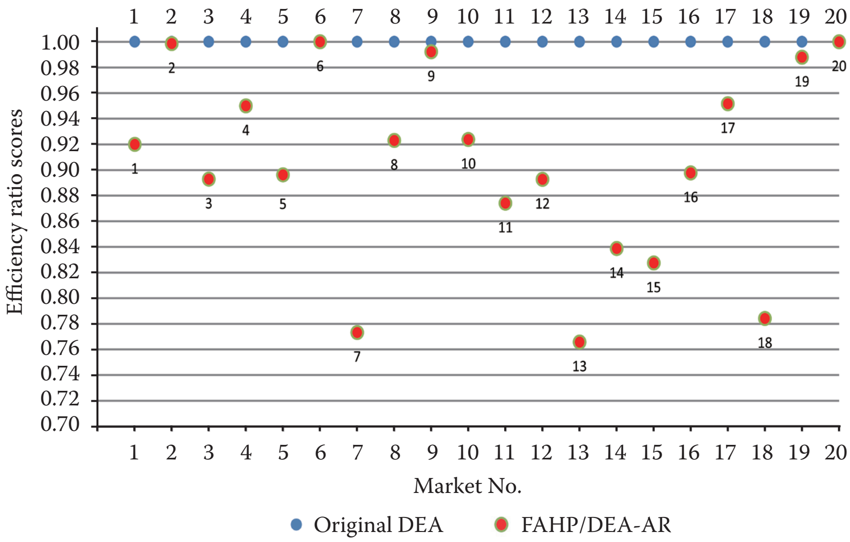

Figure 2. Comparisons of efficiency ratio scores for 20 markets

Source: authors‘ elaboration

FAHP/DEA-AR model analysis

After applying the AR processes, the number of efficient companies with an index value of 1 was reduced from 20 to 2, the DMUs 6 and 20 (Figure 2). The FAHP/DEA-AR model (hereafter "the integrated model") with weighted factors provides more details on input/output productivity and the overall performance evaluation in MACs.

When observing the predicted values of the remaining 18 markets with an efficiency index less than 1, we find that the efficiency results calculated by the in-

Table 7. Statistical Results of FAHP/DEA-AR model

Meat market	Original DEA		FAHP/DEA-AR		Efficiency decomposition		Projection (%)		Cluster category
	score	rank	score	rank	auction	slaughter	auction	slaughter	
1	1	1	0.920	10	0.749	0.171	–9	86	A
2	1	1	0.999	3	0.919	0.079	–12	146	A
3	1	1	0.893	13	0.761	0.132	7	41	A
4	1	1	0.950	7	0.727	0.223	4	10	B
5	1	1	0.896	12	0.749	0.147	3	57	A
6	1	1	1.000	1	0.814	0.186	0	0	A
7	1	1	0.773	19	0.729	0.044	–12	712	B
8	1	1	0.923	9	0.837	0.086	–8	163	A
9	1	1	0.992	4	0.841	0.151	–3	24	A
10	1	1	0.924	8	0.780	0.144	3	38	A
11	1	1	0.874	15	0.592	0.283	2	41	C
12	1	1	0.893	14	0.678	0.215	–5	65	B
13	1	1	0.766	20	0.722	0.044	–3	581	B
14	1	1	0.839	16	0.700	0.138	16	34	B
15	1	1	0.827	17	0.703	0.124	7	98	B
16	1	1	0.898	11	0.792	0.106	3	75	A
17	1	1	0.952	6	0.581	0.371	4	7	C
18	1	1	0.784	18	0.655	0.130	–8	207	B
19	1	1	0.988	5	0.417	0.571	13	–7	D
20	1	1	1.000	1	0.471	0.529	0	0	D
Average	1	–	0.905	–	0.711	0.194	0	119	–

FAHP/DEA-AR model – integrated model

Source: computed by this study

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tegrated model can effectively assess the importance of the contribution of various input and output factors in the market, and improve the efficiency analysis for the market. This result can help decision-makers to more comprehensively examine the adjustments of input-output projects, as well as provide a comparative study between markets, showing that the use of integrated models is indeed superior to the original DEA models.

Table 7 provides results on the efficiency for the original DEA, the integrated model, efficiency decomposition, projections, and the clustering application. Service revenues from auctions and from slaughtering are two primary incomes for MACs. First, after applying the AR approach with a FAHP rating framework, statistical findings can be used not only to reduce the number of efficient DMUs from 20 to 2, but also to project output enhancements by examining revenue sources and operation scale. Next, efficiency can be decomposed into two parts with revenue sources. As can be seen in Table 7, the current meat market efficiency mainly comes from the auction business, but in many markets, due to the high proportion of this income, it is unsuitable for sustainable operation.

Having adjusted the importance of the input-output project on the integrated model by considering the expert opinions, the meat market companies can then adapt the operating resources of the auction service to the slaughter service project by a reasonable adjustment in order to improve the overall company performance.

Cluster analysis

With regards to efficiency decomposition and integrated model performance evaluation, hierarchical cluster analysis was used to identify the optimal number of clusters based on between-group linkage helps to obtain detailed characteristics of each variable by representing a specific state of dependence across sections (Verdier 2016). Figure 3 presents a general form of dependence in the cluster analysis (Mooi and Sarstedt 2011). Twenty DMUs are divided into four clusters, with eleven DMUs categorized in Cluster A, DMUs 7, 13, 14, 15, and 18 in Cluster B; DMUs 11 and 17 in Cluster C; and DMUs 19 and 20 in Cluster D.

Projections of two revenue sources for each DMUs in the four clusters are shown in Figure 4. Most MACs are advised to improve efficiency performance by increasing their income from providing more slaughtering services. Statistical findings on positive and high pro-

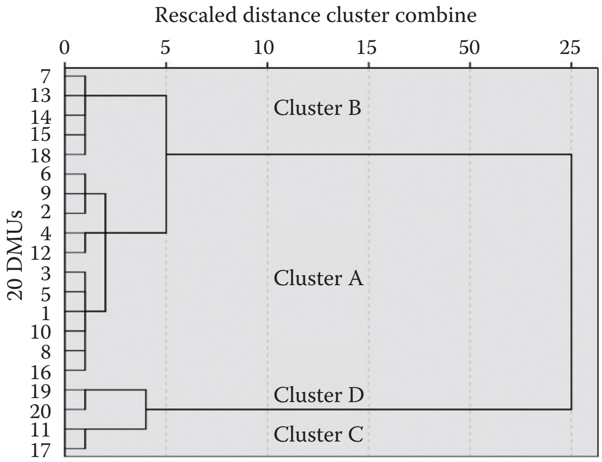

Figure 3. Cluster analysis with Ward method

Source: authors‘ elaboration

jection values on Y_2 imply that an increase in slaughter-related revenue may enhance market efficiency performance. In other words, receiving additional revenues by utilizing slaughter facilities rather than by providing auction services and distributing auction animals may allow most MACs in Taiwan to achieve higher economic efficiency.

All twenty MACs in Taiwan, categorized into four sub-groups based on the Ward analysis, are plotted in a two-dimensional diagram with the axes representing the two sources of revenues, from auctions and from slaughtering (Figure 5). DMU19 and DMU20, which are assorted in Cluster D, are defined as the slaughtering-oriented group based on the high slaughter-related earnings. When the efficiency is decomposed into two income sources, auction services and slaughtering, the two abovementioned DMUs are the only companies where the efficiency indices from slaughter-related income are higher than from auction income (0.571 > 0.417 and 0.529 > 0.471). Other two market companies receive the same amount of revenues from the two sources: DMUs 11 and 17 in Cluster C, defined as the sub-slaughter group, presenting relatively higher income efficiency after decomposition. The two market companiess can improve the efficiency by raising the income from providing further slaughter-related services after auctions even though their operation scale is relatively small.

Cluster A, defined as the high-auction group, with eleven primary MACs, mainly receive revenues from auction services. From the results of the decomposition of efficiency, the Cluster A MACs present high ratio from auction service (0.919~0.678) and low value from slaughter-related work (0.186~0.086). Results

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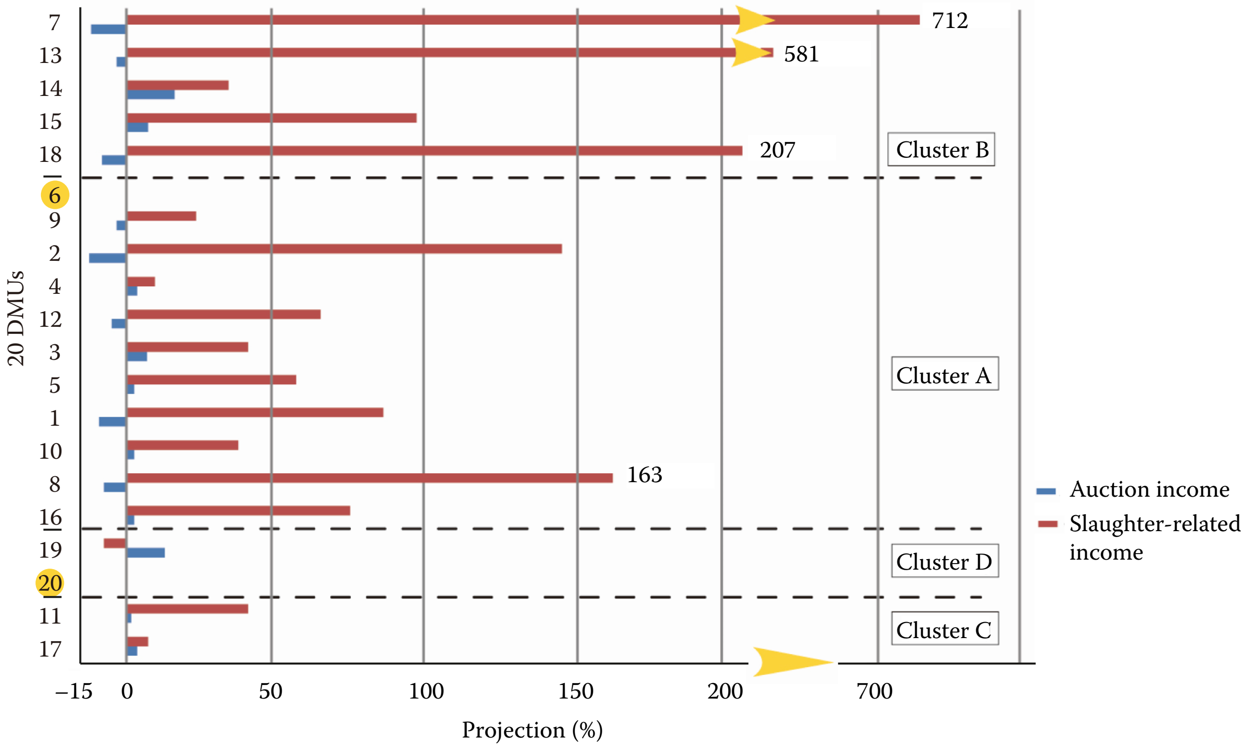

Figure 4. Projection of two revenue sources for 20 markets

decision making units (DMUs) 6 and 20 are two best efficiency performing markets with the score at 1 for DEA-AR model with highlight; arrows mean the scales of projection for DMU 7 and 13 are different from others due to the convenience of display

Source: authors' elaboration

show that DMUs in this cluster are the MACs with high-efficiency performance.

Other five DMUs, which are grouped in Cluster B, are diagnosed as the ones at relatively low-efficiency

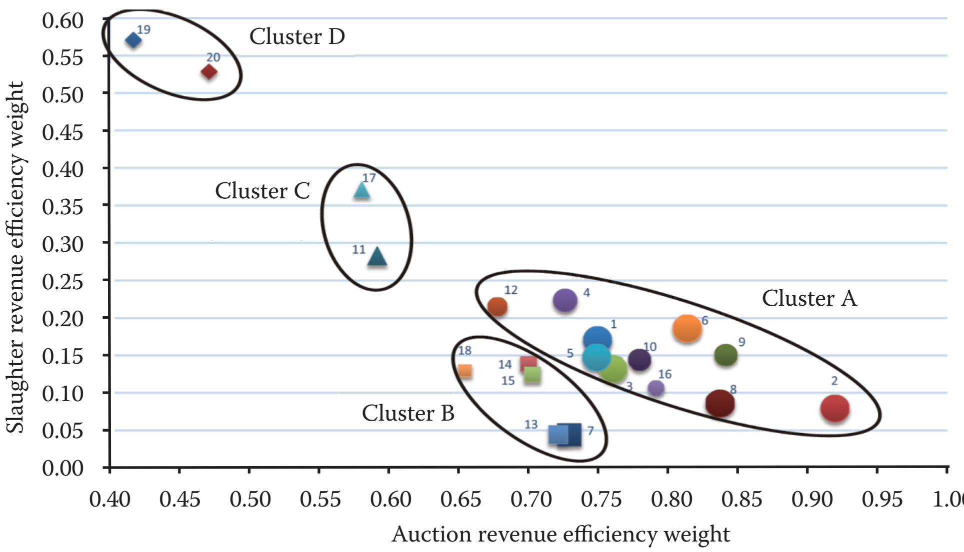

Figure 5. Income efficiency decomposition of four cluster categories

circles and specific shapes represent the numbered meat auction companies (MACs) in separated groups

Source: authors' elaboration

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performance with an uneven portion of auction revenue. Significant differences between the two revenues are observed in this cluster. A large portion of auction incomes may imply a reduced efficiency in facility utilization for slaughter facilities, and lower income was earned from the slaughtering service provided by these MACs.

DISCUSSION AND CONCLUSION

This paper employed twenty meat auction companies in Taiwan to apply the AR approach by restricting the range of input-output weights with experts' opinions. From interviewing 34 experts by a FAHP-type questionnaire, we generated new boundaries for lower and upper limits by weighting each variable for each input and output.

Other than the indifferent result from the original DEA model with all extreme-efficient values at 1 for all market performance, the outcomes in this study with the AR technique indicated that only two DMUs could reach the critical standard by applying the integrated model with expert responses under the business concern. The result with different weights on variables show that the integrated model provides more useful and diagnostic results than the original DEA (Liu and Chuang 2009; Taylor et al. 1997; Yu and Lee 2013).

After decomposing the efficiency from two service revenues provided by MACs, the projection values after business adjustments for each market company indicated that increased income from slaughter-related services might be helpful to improve market efficiency. It shows that the high investment equipment of the Taiwanese meat market in the slaughtering business is not fully reflected in the revenue, and the low utilization rate may be the main reason. The difference in revenue between auction and slaughtering sources is significant. It affects the allocation of personnel and facilities and becomes a hidden worry in the overall auction market. With the decomposition of the two revenue sources, research results reveal that the market companies with high auction revenue should increase their revenues from slaughter-related services to achieve better and more consistent performance.

In the face of fierce competition in the competitive spatial market, market managers should consider taking the operation strategy not by multiplying the market size, but by increasing the total revenues by levying the input resources for providing the auction and slaughter services with balance.

The limitation on determining the weights of related factors through expert opinions should be addressed. With this concern, this study invited experts from different marketing stages and positions to represent the real market situation. Next, even though the number of operators in the wholesale auction market is not large, analysis of the meat market is meaningful for the spatial competition behavior of various companies. By integrating models and expert opinions, this study does make a significant analysis of the different cost and revenue conditions of a company that will indeed lead to a mixed performance in the auction market, and we also propose appropriate business strategies for improvement.

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