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Data Envelopment Analysis in Evaluating the Technical and Scale Efficiencies of Micro Enterprises in Sabah

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Abstract

This paper evaluates the performance of 26 micro enterprises in Sabah under the bakery sector using the Data Envelopment Analysis. The performance indicators which are the inputs and outputs for this study are chosen based on past studies. The Charnes, Cooper and Rhodes (CCR) Data Envelopment Analysis will give the Overall Technical Efficiency score whereas the Banker, Charnes and Cooper (BCC) Data Envelopment Analysis will reveal the Pure Technical Efficiency score for all micro enterprises. From there, the Scale Efficiency is obtained by finding the ratio of the relative efficiency score given by both CCR and BCC Data Envelopment Analysis. This paper also evaluates the inefficient micro enterprises in terms of the improvements in inputs and outputs to become more efficient as well as identifying which efficient micro enterprises will be used as a reference set for these inefficient micro enterprises to become more efficient.

Keywords: Data Envelopment Analysis, Scale Efficiency, Technical Efficiency, Micro enterprises, Decision Making Units

Introduction

Performance analysis is imperative to remain relevant in an age of competitiveness and advancements (Zhu, 2003), coupled by the fact that the Small and Medium Enterprises are one of the vital backbone in a nation's economy (Büyükkeklik, Dumlu and Evci, 2016), it comes to no surprise that measurement of the SMEs performance in terms of their productivity and relative efficency is still a relevant study not only in Economics, but also in the field of medicine (Asandului, Roman, Fatulescu, 2014), higher education (Zulkifli, Hashim, Sulaiman and Topimin, 2024), finance (Othman et al., 2016) and sports analysis (Barholomew and Collier, 2011). Sony, Sukarno and Ichsan (2006) have stated that evaluating or estimating performance is to judge an organisations' value chain by their various activities. However, this method only showcases the firm's position rather than their usage of resources or inputs and production or outputs. This study will demonstrate the effectiveness of the Data Envelopment Analysis (DEA) model in measuring both the Overall Technical Efficiency (OTE) and Pure Technical Efficiency (PTE) of a firm. From there, the Scale Efficiency (SE) which is derived from both PTE and OTE will help inefficient firms to become more efficient and productive in relation to their efficient peers. In the case of Malaysia, the Micro, small and Medium Enterprise (MSME) has greatly contributed towards the nation's Gross Domestic Product (GDP) as shown by the Department of Statistics Malaysia (DOSM) in 2023 where the MSME has contributed RM520 billion in the nation's GDP (DOSM, 2023). Furthermore, the Services and Manufacturing (S&M) sectors which includes the bakery enterprises makes up the bulk of the S&M sectors which makes up around 84.8% (DOSM, 2023). Therefore, it is crucial to find determine whether these vital sectors are operating at an efficient level by conducting an efficiency and performance analysis on these sectors. The main objective of this paper is to use the DEA model to identify which firms are relatively efficient in terms of their performance as well as finding the SE based on the results from the DEA model which will be discussed in the fourth section. Section two will discuss on the relevant past studies and performance indicators that are suitable for this study whereas the third sector will discuss on the data used for this study and the mechanism of the DEA model. Lastly, the fifth and final section will conclude this paper.

Literature Review

In this section, the definition of MSME in Malaysia as well as past studies will be discussed to demonstrate the rich history of the DEA model in analysing the performance of firms. SME within the Malaysian framework is classified under three enterprises which are micro, small and medium sizes. The table below details the definition on each enterprise in terms of their number of employees and sales within the manufacturing sector (SMECorp, 2020).

Table 1
Definition of the Malaysian MSME

Enterprises	Micro	Small	Medium
Sales/Number of employees	RM300,000 OR less than five employees	RM300,000-RM14,999,999 OR 5-74 employees	RM15,000,000 – RM49,999,999 OR 75 to 199 employees

Zapata-Guerrero, Mayer-Granados & Charles Coll (2020) utilised both BCC and CCR DEA in measuring efficiency of 25 business incubators in a Mexican University from 2012 to 2014. From the 25 firms, 13 of them were shown to be relative efficient and the best performers when compared to their peers. The input for these firms were identified as the total number of resources, employees and available floor space whereas the productions were identified as annual rate of graduates, annual survival rate and annual employment growth rate. Yeh and Chang (2019) conducted a performance analysis of 128 firms in the information technology (IT) industry in Taiwan from 2008 to 2015 using Categorical DEA. This study has identified the inputs as the research and development (R&D) expenditure and selling, general and administrative expenditure whereas the outputs were identified as total revenue as well as total patents. The study concluded that the lack of patents and technological learning are the key sources of inefficiencies.

Setiawan, Indiastuti and Indrawati (2016) have used a three-step DEA model to measure the technical efficiency of 100 SMEs in Bandung in 2014 as well as exploring the external factors that can have an impact on their efficiency. The number of competitors, material used, labour cost and capital were used as the inputs whereas the revenue is the only output. Results showed that the efficiency score of SMEs in Bandung has increased from 0.39 to 0.708 which demonstrated the significant effect external factors have on SMEs. Büyükkeklik, Dumlu and Evci (2016) had also conducted a study on 17 SMEs in 2011 to 2014 using the CCR DEA as its model for performance analysis. The inputs were short-term liabilities, long-term liabilities as well as equity value of Turkish SMEs whereas sales revenue and net profit values were identified as the outputs. Results showed that five SMEs were efficient in 2011, four in 2012 and 2013, and five in 2014.

Lee (2013) have also conducted a study in the Korean SMEs from 2007 to 2012 to determine the efficiency, growth and stability of Korean shipyards with qualifications of SME with number of labour, capital and company age used as inputs whereas sales and net profit were used as outputs. Results show that there were only a handful of shipyards that are operating at an efficient level. Purwanto, Manongga and Pakereng (2014) have implemented both CCR and BCC DEA to find the SE of 31 tofu enterprises in Salatiga, Indonesia. The inputs are identified as the number of employees, production space, soybean produced and expenses whereas the sales and daily gross profit were identified as the outputs. Results showed that eight SMEs were technically efficient whereas the remaining 23 were not. The table below summarises the past studies with their corresponding inputs and outputs that are used in their studies.

Table 2
Summary of Past Studies

Study	Country	DEA Model	Input Variables	Output Variables
Zapata-Guerrero, Mayer-Granados & Charles Coll. (2020)	Mexico	• BCC • CCR	• Total number of resources • Number of employees • Total floor space available	• Annual rate of graduates • Annual survival rate • Annual employment growth rate
Yeh and Chang (2019)	Taiwan	• Categorical DEA	• R&D • SG&A expenses	• Total patents • Total revenue
Setiawan, Indiastuti and Indrawati (2016)	Indonesia	• Three-stage Slack-Based DEA	• Number of competitor • Material used • Labour cost • Capital	• Revenue
Büyükkeklik, Dumlu and Evci (2016)	Turkey	• CCR	• Short-term liabilities • Long-term liabilities • Equity value of	• Revenue • Net profit values

			Turkish SMEs	
Lee (2013)	South Korea	• BCC • CCR	• Number of labour • Capital • Company age	• Sales • Net profit
Purwanto, Manongga and Pakereng (2014)	Indonesia	• BCC • CCR	• Number of employees • The amount of • Deposit • Cost	• Sales • Daily gross profit

From the past studies. It is determined that capital and number of employees will be identified as the inputs whereas the total sales and profit will be the outputs. The rationale behind this is that when comparing to the scale of operation between micro, small and medium enterprise based on the definition given by SMECorp. Microenterprises have the smallest scale and therefore their questions should be relatively straightforward. The table below shows the summary of the inputs and outputs used in this study.

Table 3
Inputs and Outputs Chosen for Analysis

INPUTS (x_i)	**OUTPUTS (y_r)**
Capital	Total sales
Full time worker	Profit

Data Preparation and the DEA Models
The data that is used in this study is primer in its nature and comprises of 23 microenterprises that are involved in the bakery sector in Sabah, Malaysia. Both CCR and BCC DEA model will be analysed using RStudio version 2024.04.1 to determine the performance and relative efficiency of microenterprises in Sabah, Malaysia. Prior to analysis and performance evaluation, the data must be adequate in order to increase the discriminatory power of the DEA model (Charkes, Aparicio and Zhu, 2019). The tables below show the microenterprises and their respective inputs and outputs as well as the rule of thumb minimum amount of data needed to have a DEA model that has a sufficient discriminatory power to determine which microenterprises are efficient and which are not.

Table 4
Data for 23 Microenterprises

DMU	x_1	x_2	y_1	y_2
DMU1	31867.9	2	57075	25207.1
DMU2	5000	2	40,000	18000
DMU3	1224	1	4700	2750
DMU4	2000	1	1500	800
DMU5	12000	1	21567	9567
DMU6	25000	2	50000	18000
DMU7	400	1	800	400
DMU8	50000	2	3800	5000
DMU9	3000	2	70000	10000
DMU10	10000	2	50000	5000
DMU11	10000	3	30000	15000
DMU12	5000	1	7000	2000
DMU13	2000	1	2000	1000
DMU14	1250	1	1650	750
DMU15	50000	2	6402	0
DMU16	13000	2	35000	10000
DMU17	1000	1	5000	2000
DMU18	50000	4	20000	10000
DMU19	2000	1	10000	7000
DMU20	80,000	3	150,000	50,000
DMU21	2500	1	3800	1300
DMU22	2000	1	1000	2000
DMU23	40,000	3	50,000	35,000

Table 5
Minimum Data Required for DEA Model

Author	**Rule of Thumb**
Golany and Roll (1989), Homburg (2001)	$2(x+y)$ = The minimum amount of data 2(2+2) = 8
Raab and Lichty (2003), Friedman and Sinuany-Stern (1998), Bowlin (1998) Nunamaker (1985), Banker Et Al. (1989)	$3(x+y)$ = The minimum amount of data 3(2+2) = 12
Dyson Et Al. (2001)	$2(xy)$ = The minimum amount of data 2[(2)(2)] = 8
Boussofiane (1991)	(xy) = The minimum amount of data [(2)(2)] = 4

From the table above, it is sufficient to say that the amount of data used in this study is more than sufficient to ensure a model with a decent discriminatory power.

DEA is a non-parametric method for measuring the relative efficiency of units and their peers. In the field of DEA, the units that would be analysed based on their performance and relative efficiency score would be classified as Decision Making Units (DMUs). In this case, the DMUs are known to be the microenterprises. The CCR DEA model which was introduced by Charnes, Cooper and Rhodes (1978) assumes the constant return to scale (CRS) which is defined as any proportionate change in all input will cause a proportionate change in output that is equal (Eatwell, 2008). The input-oriented CCR DEA formula in its envelopment model is as follows:

$$\theta_{input}^{0*} = Min\ \theta_{input}^{0}$$

Subject to:

$$\sum_{i=1}^{m} x_{ik}\lambda_k \leq \ \theta_{CCRinput}^{0} x_{i0}\ (i = 1,2, \dots, m)$$
$$\sum_{r=1}^{s} y_{rk}\lambda_k \geq \ y_{r0}\ (r = 1,2, \dots, s)$$
$$\theta_{CCR}^{0}, \lambda_k \ \geq 0$$

(1)

Where:
θ_{input}^{0*} = Input-oriented efficiency score
x_{ik} = Virtual input for DMU_k where $i = 1,2, \dots, m$
$\mathrm{y_{rk}}$ = Virtual output for DMU_k where $r = 1,2, \dots, s$
x_{i0} = Input under evaluation
$\mathrm{y_{r0}}$ = Output under evaluation
λ_k = Weight for DMU_k where $j = 1,2, \dots, n$

The CCR model measures the Overall Technical Efficiency (OTE) of a DMU where the OTE helps to distinguish which DMUs are efficient and which DMUs are not based on both managerial inefficiencies and the size of operations (Kumar and Gulati, 2008). OTE is obtained by finding the product of the Pure Technical Efficiency (PTE) and the Scale Efficiency (SE):

$$Overall\ Technical\ Efficiency = \ Pure\ Technical\ Efficiency\ \times Scale\ Efficiency$$

(2)

The BCC DEA, on the other hand, assumes the variable return to scale where it introduces a new constriction into the CCR formula which is:

$$\sum_{k=1}^{n} \lambda_\mathrm{k} = 1$$

(3)

Introduced by Banker, Charnes and Cooper (1984), the variable return to scale is a phenomenon where an increment in inputs used does not equate to a proportionate change in the output and it can be classified as either being constant, increasing (IRS) or decreasing return to scale (DRS). We can determine whether the VRS is decreasing or increasing by observing the previous constraint:

$$If \sum_{j=1}^{n} \lambda_j^* > 1, then\ DMU_0\ is\ DRS$$
$$If \sum_{j=1}^{n} \lambda_j^* < 1, then\ DMU_0\ is\ IRS$$

The BCC DEA measures the PTE of a DMU which is defined as the measurement of inefficiencies due to managerial underperformance only without taking the size of operations into account (Kumar and Gulati, 2008). However, the SE is vital in determining the efficiency of a DMU as it indicates whether or not the size of operations is optimal so much so that any modifications made to its size will cause the DMU to become less efficient (Aparicio and Santin, 2024). Recalling back from formula 2, we can obtain the scale efficiency by finding the ratio of the DMU based on its CCR and BCC model.

$$Scale\ Efficiency = \frac{\theta_{CCR}^{0*}}{\theta_{BCC}^{0*}} \tag{4}$$

Another advantage of using the DEA model is that the recommendation for improvement of inefficient DMUs can be achieved by taking slacks into account which can be seen in the Additive CCR DEA below:

$$Max \sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+$$

Subject to:

$$\sum_{i=1}^{v} x_{ij}\lambda_j + s_i^- = x_{i0} \quad i = 1,2,\ldots,v$$
$$\sum_{r=1}^{u} y_{rj}\lambda_j - s_r^+ = y_{r0} \quad r = 1,2,\ldots,u$$
$$\lambda_j, s_i^-, s_r^+ \geq 0 \tag{5}$$

Where:
s_r^+ = Shortfall slacks
s_i^- = Excess slacks

These slacks represent the values that the DMUs ned to lose or gain in order to become more efficient. Shortfall slacks represent the values that exist that the input needs to lose in order to become more efficient whereas the shortfall slacks represent how much more the output of a DMU that needs to increase in order to become more efficient. Since we are dealing with the input oriented CCR DEA. The formula for the value of the recommended input after taking the excess slacks into account is as follows, where s_i^{-*} and s_r^{+*} identifies as the optimal input and output slacks accordingly.:

$$x_{io}^* = \theta_{CCRinput}^{0} x_{i0} - s_i^{-*} \tag{6}$$

The formula for the value of the recommended output according to the input oriented CCR DEA is as follows

$$y_{ro}^* = y_{r0} - s_r^{+*} \tag{7}$$

Results and Analysis

Table 6 shows the efficiency score for all DMUs. From the table below, it is deduced that DMU2, DMU9 and DMU20 have the best relative efficiency score out of all measured peers and therefore will be used as the benchmarks for other inefficient DMUs. For example, DMU1 will refer to DMU2 and DMU20 for it to become more efficient. another important thing to note is that the PTE score will always be equal or more than the PTE, this is because of the CCR or CRS DEA nature that takes both PTE and SE into account hence it is more constricting than the PTE or BCC DEA (Ng and Ahmad, 2012). DMU10 has a technical efficiency score of

0.7894, this means that it has a technical efficiency of 78.94% and therefore would have to reduce their input usage by 21.06%. The OTE score refers to the overall relative efficiency score for a DMU. For example, DMU2 is efficient overall as both PTE and SE are efficient where as DMU15 is technically efficient but scale inefficient and therefore it is classified as OTE inefficient. SE refers to the impact of scale size on the DMU level of productivity. For instance, DMU 20 has an SE of 1 which means that any scale of inputs and outputs in a linear way will not cause any increment or decrement on the efficiency. DMU18, on the other hand, has a high SE but relatively low OTE and PTE. This means that DMU18 is overall inefficient due to their managerial practice which is evaluated under PTE rather than the scale of operations.

Table 6
The Efficiency Score for All Microenterprises

DMU	OTE	PTE	SE	Reference Set
DMU1	0.9503	0.9787	0.971	{2,20}
DMU2	1	1	1	{2}
DMU3	0.6241	1	0.6241	{2)
DMU4	0.1111	1	0.1111	{2}
DMU5	0.7963	1	0.7963	{2,20}
DMU6	0.7514	0.8129	0.9243	{2,9,20}
DMU7	0.2778	1	0.2778	{2}
DMU8	0.1549	0.5	0.3098	{2,20}
DMU9	1	1	1	{9}
DMU10	0.6741	0.7894	0.8539	{9,20}
DMU11	0.5397	0.562	0.9603	{2,20}
DMU12	0.2386	1	0.2386	{2,9,20}
DMU13	0.1389	1	0.1389	{2}
DMU14	0.1667	1	0.1667	{2}
DMU15	0.0653	1	0.0653	{9,20}
DMU16	0.563	0.6614	0.8512	{2,9,20}
DMU17	0.5581	1	0.5581	{2,9}
DMU18	0.2054	0.2554	0.8042	{2,20}
DMU19	0.9722	1	0.9722	{2}
DMU20	1	1	1	{20}
DMU21	0.1597	1	0.1597	{2,9,20}
DMU22	0.2778	1	0.2778	{2}
DMU23	0.9381	1	0.9381	{2,20}

Table 7 shows the returns to scale for each DMUs. This is an important aspect in determining the operation size is optimal or not. An increasing returns to scale means that the microenterprise can continue to increase their input usage as it can produce more potential outputs where as a decreasing return to scale denotes that the operating size of a microenterprise must decrease its input usage as it is wasting its resources. In this study, it is interesting to note that all of the DMUs with the exception to DMU23 that are not efficient have the potential to increase their scale size as doing so will increase their output. On the other hand, DMU23 will have to decrease its operating scale in order to increase efficiency

Table 7
The Nature of RTS for Each Microenterprises

DMU	$\sum_{k=1}^{n} \lambda_k^*$	RTS
DMU1	0.7743	Increasing
DMU2	1	Constant
DMU3	0.1528	Increasing
DMU4	0.0444	Increasing
DMU5	0.346	Increasing
DMU6	0.6742	Increasing
DMU7	0.0222	Increasing
DMU8	0.1068	Increasing
DMU9	1	Constant
DMU10	0.6429	Increasing
DMU11	0.8003	Increasing
DMU12	0.1146	Increasing
DMU13	0.0556	Increasing
DMU14	0.04167	Increasing
DMU15	0.045	Increasing
DMU16	0.529	Increasing
DMU17	0.1163	Increasing
DMU18	0.3541	Increasing
DMU19	0.3889	Increasing
DMU20	1	Constant
DMU21	0.0796	Increasing
DMU22	0.1111	Increasing
DMU23	1.1969	Decreasing

Table 8 and 9 shows the slacks for all DMUs as well as the recommended inputs and outputs for all potential improvements for inefficient DMUs respectively. Note that DMU2, DMU9 and DMU20 do not have slacks as they are all relatively efficient and do not need any recommendations in their inputs or outputs. DMU1 has no input slacks but recalling equation (6), there is still room for improvements in the slacks which is why the recommended value for the second input in DMU1 changes slightly to 1.901 which stills rounds off to 2 as it is referring to the number of employees. DMU7 has a shortfall slack of 88.89 in the first output which is the total sales. Recalling equation (7), this basically means that DMU7 needs to increase their total sales by RM88.89 in order to become more efficient

Table 8
Slacks for all Inefficient DMUs

DMU	s_1^{-*}	s_2^{-*}	s_1^{+*}	s_2^{+*}
DMU1	0	0	12637.38	0
DMU2	0	0	0	0
DMU3	0	1	1411.11	0
DMU4	0	1	277.78	0
DMU5	0	0	3750.95	0
DMU6	0	0	0	0
DMU7	0	1	88.89	0
DMU8	0	0	11050.43	0
DMU9	0	0	0	0
DMU10	0	0	0	3928.57
DMU11	0	0	4057.07	0
DMU12	0	0	0	0
DMU13	0	1	222.22	0
DMU14	0	1	16.67	0
DMU15	0	0	0	2076.32
DMU16	0	0	0	0
DMU17	0	1	0	0
DMU18	0	0	6628.90	0
DMU19	0	1	5555.56	0
DMU20	0	0	0	0
DMU21	0	0	0	0
DMU22	0	1	3444.44	0
DMU23	0	0	44131.24	0

Table 9
Recommended Inputs and Outputs for all Inefficient DMUs

DMU	x_1^*	x_2^*	y_1^*	y_2^*
DMU1	30284.07	1.901	69712.34	25207.1
DMU2	5000	2	40000	18000
DMU3	763.90	0.3056	6111.11	2750
DMU4	222.22	0.0889	1777.78	800
DMU5	9556.02	0.7963	25317.95	9567
DMU6	18784.67	1.5028	50000	18000
DMU7	111.11	0.0444	888.89	400
DMU8	7745.73	0.3098	14850.43	5000
DMU9	3000	2	70000	10000
DMU10	6741.07	1.3482	50000	8928.57
DMU11	5397.02	1.6191	34057.07	15000
DMU12	1193.22	0.2386	7000	2000
DMU13	277.78	0.1111	2222.22	1000
DMU14	208.33	0.0833	1666.67	750
DMU15	3265.89	0.1306	6402	2076.32

DMU16	7318.67	1.1259	35000	10000
DMU17	558.14	0.2326	5000	2000
DMU18	10269.12	0.8215	26628.90	10000
DMU19	1944.44	0.7778	15555.56	7000
DMU20	80000	3	150000	50000
DMU21	399.27	0.1597	3800	1300
DMU22	555.556	0.2222	4444.44	2000
DMU23	37523.11	2.8142	94131.24	35000

An interesting note is that despite the DMUs are being analysed using the input-oriented CCR and BCC DEA. There are slacks appearing in the outputs which are evident in most DMUs with the exception of DMU17. DMUs that are showing both excess and shortfall slacks are known to have mix inefficiencies which basically means that an alteration of inputs will result in an altered production of outputs. Despite DMU16 and DMU21 being inefficient, they have no slacks whatsoever. Recalling from Table 6, DMU16 has a PTE score of 0.6614 or 66.14%. Hence, DMU16 needs to reduce its input usage by 33.86% in order to become more efficient. DMU17 has a PTE score of 1 which means that the management of resources is already optimal however the SE score is 15.97% which means that their resources are severely underused and therefore they should increase their inputs in order to produce more outputs. An important thing to note for the second input, x_2, is that it contains the number of employees and therefore it is required to present the value in round numbers for example DMU1 is recommended to have 2 employees rather than 1.901.

Conclusions

To summarise, this paper has managed to answer the overall efficiency, management of inputs and scale size for all 23 microenterprises in Sabah's bakery sector using the CCR and BCC DEA which assumes the CRS and VRS returns to scale respectively, three DMUs were identified to be operating at an optimum level whereas the other 20 were found to be inefficient. Within these 20 DMUs that are inefficient, 19 of them are IRS in nature and the remaining DMU23 is DRS in nature. Despite DMU18 is increasing returns to scale, it has a low PTE score of 25.54% and therefore the management needs to sort out the PTE score first before moving on to the scale of operations. Other DMUs that are IRS but are efficient in terms of their PTE such as DMU22 can proceed by increasing their operation scale to increase their relative efficiency score. In conclusion, the DEA model is a suitable method in measuring the relative efficiency score of microenterprises as it can handle multiple inputs and outputs without prior assumptions. However, the selections of input and outputs must be relevant to the study and the data must be sufficient with respect to the number of inputs and outputs chosen for the study. DEA is also suitable in that it exceeds traditional efficiency calculations as it does not rely on simple ratio calculations. Future studies can explore other aspects of the microenterprises such as their ranking based on their relative efficiency score or by taking the slacks into account in determining their efficiency score which is known as the Slack Based Model; a more comprehensive model than the traditional CCR or BCC DEA due to its non-radial nature. This study serves to benefit policy makers in determining if micro enterprises are operating at a relative efficient level compared to their peers as well as identifying which enterprises are relatively inefficient in their technical, scale efficiency or both and improve inefficient enterprises according to the slacks given by the DEA model through training, financial or tax relief aids shown by Ayub, Mifli and Majid (2022), Fajnzylber, Maloney and Montes-Rojas (2010) and Karlan and Zinman (2011).

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