Performance Evaluation Using PCA and DEA: a Case Study of the Micro and Small Manufacturing Industries in Indonesia

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ABSTRACT

Companies frequently evaluate their business performance based on existing advantages and shortcomings. Data envelopment analysis (DEA) is a useful decision-making tool for doing so; it evaluates the relative efficiency of a department or unit as a decision-making unit (DMU). It is also a powerful tool for studying production limits by using multiple inputs and outputs. Principal component analysis (PCA) is a technique for simplifying a data set by reducing multidimensional data sets to lower dimensions for analysis; it reduces the dimensions of input and output variables. This study evaluated the performance of the micro and small manufacturing industries (MSMI) in Indonesia using a combination of Principal Component Analysis and an Input-Oriented DEA Envelopment Model. Development of micro and small manufacturing industries in Indonesia is inhibited by various factors. Based on our results, we determined that the following factors were causative for MSMI in Indonesia: marketing, human resources, materials, machinery, capital and finance, product, technology, support, research & development, distribution, promotion, competitors, and policy.

Keywords: Performance evaluation, Micro and small manufacturing industries, Variable selection, PCA, DEA

INTRODUCTION

Evaluating business performance is important to a company's growth and development. Performance evaluations aim to: (i) internally evaluate a business' current operations and (ii) compare this performance to similar companies and best practices. This will help a company: (i) understand its strengths and weaknesses, (ii) better organize its business to meet customer demands and requirements, and (iii) define business opportunities to improve operations and activities by creating new goods, services, and processes (Cook & Zhu, 2008).

The micro and small manufacturing industries (MSMI) in Indonesia contribute to gross domestic product (GDP), create employment, and help distribute local community welfare and reduce the income gap (Putri et al., 2016a; Putri, 2016b; Putri & Abdulrahim, 2017a; Putri et al., 2017b). In 2014, Indonesia had 3.5 million MSMI, of which more than 90% were classified as micro (BPS, 2014). Several factors hinder MSMI business development: poor marketing and promotion, producing goods mismatched to market requirements, poor quality of raw materials, inadequately trained or educated employees, inappropriate fabrication facilities, manufacturing technology that does not meet modern requirements, inadequate access to capital, dependence on family and relatives, costly production, minimal innovation, inadequate distribution networks (Putri & Abdulrahim, 2017a).

This study evaluated MSMI performance in Indonesia using two methods: principal component analysis (PCA) (Zhu, 1998; Adler & Yazhemsky, 2010; Yoshino & Hesary, 2014) and data envelopment analysis (DEA) (Cook & Zhu, 2008) to help identify the problems the sector faces in developing their businesses and to identify factors to help them better compete, particularly in the face of global competition, and sustain their business.

METHODOLOGY

Theoretical background

Data envelopment analysis (DEA). Data envelopment analysis (DEA) is useful for evaluating the relative performance efficiency of departments or units as decision-making units (DMU) and to determine production limits using multiple inputs and outputs – all while reducing the need for subjective factors. Compared to other methods, its biggest advantages are that it is (i) technical, (ii) does not require a known production function with parameters in advance, (iii) is an excellent model for comparing the efficiency of different distribution networks (Yuzhi & Zhangna, 2012), and (iv) is simple to calculate and program.

Typically, businesses try to minimize inputs, such as costs, manpower, and materials; and maximize outputs, such as products, revenue, and profit. The input and output variables are selected before applying DEA. DEA uses decision making units (DMUs) to represent any business operation, process, or entity that converts multiple inputs into multiple outputs. The Data Envelopment Analysis model, created by Charnes, Cooper, and Rhodes (Charnes et al., 1978), provides a way to identify this piecewise linear frontier. Mathematical programming tools are used to identify non-dominated DMUs and create piecewise linear sections that make up the frontier. The DEA frontier is identified and fulfilled after identifying the efficient DMU; i.e., the efficient frontier consists of a DMU that performs well. By comparing each DMU with the identified efficient frontier, the DEA provides: (i) an efficiency rating (score) for each DMU, (ii) an Efficiency Reference Set (ERS), or peer group, for each unit that is not efficient; and (iii) targets for each DMU to achieve efficiency. The DEA provides information on how the inputs could be optimized and outputs improved if the DMU were efficient – in essence, guidelines to improve productivity and performance by using the efficient frontier.

Selection of input and output variables for DEA. With the DEA model, it is important to carefully select the input and output variables (Paradi et al., 2004). Principal component analysis (PCA) helps reduce the dimensions of these variables. PCA is a standard data reduction technique that extracts data, removes redundant information, highlights hidden features, and visualizes the main relationships that exist between observations. It is a technique for simplifying a data set by reducing multidimensional data sets to fewer dimensions for analysis (Yoshino & Hesary, 2014). Zhu (1998) was the first to use PCA to evaluate the efficiency of a DEA model by combining variables from multiple inputs and outputs. Adler and Yazhemsky (2010) reduced the dimensionality of the variables by combining PCA and DEA.

Input-oriented DEA envelopment model. There are different ways to displace the inefficient DMUs onto the frontier. This can be approached from two basic directions – those oriented to inputs or outputs. One tries to reduce inputs relative to fixing outputs at current levels. The other tries to increase outputs relative to fixing inputs at current levels (see Fig. 1).

The following DEA model (1) is oriented to inputs, which are minimized while outputs are fixed at current levels:

$$\theta^* = \min \theta$$

subjected to the following restrictions:

$$\begin{aligned} &\sum_{j=1}^{n} Xij\ \lambda j \le \theta\ Xio\ , i = 1, \ldots, m \\ &\sum_{j=1}^{n} Yrj\ \lambda j \ge Yro, r = 1, \ldots, s \\ &\sum_{j=1}^{n} \lambda j = 1 \\ &\lambda j \ge 0 \quad j = 1, \ldots, n \end{aligned} \tag{1}$$

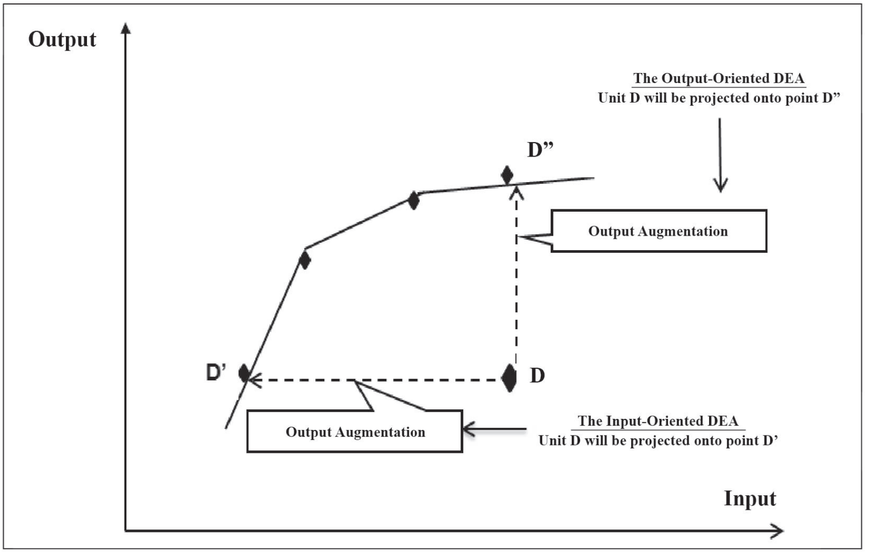

Figure 1. Formation and change of DEA frontier by input and output variables.

where DMU_0 is one of the *n* defined DMUs; X_{i0} and Y_{r0} are the i^{th} input and the r^{th} output for DMU_0, respectively; and λ_j present unknown weights, where $j = 1,\ldots, n$ determines the DMU number. Here, θ is a solution variable, representing the DEA *effectiveness score*. Because $\theta = 1$, it is a feasible solution for model (1), with *the optimal value*, $\theta^* \leq 1$. If $\theta^* = 1$, then the current input levels cannot be decreased proportionally; this shows the location of DMU_0 on the frontier. If $\theta^* < 1$, then DMU_0 is found by the frontier and inputs can be decreased by the same proportion of θ^*; thus, the same output levels can be achieved with fewer inputs (Cook & Zhu, 2008).

Principal component analysis (PCA). In various applications of DEA, the number of input and output variables exceeds the number of decision-making units (DMU). This is an important pitfall. Although increasing the number of DMUs can overcome this problem, this is impractical if the available DMUs are limited. In these cases, it is more reasonable to reduce the number of input and output variables (Cooper et al., 2007; Tolooa & Babaeeb, 2015). PCA helps simplify the data by removing the data from multidimensional data sets by: (i) removing data with excessive information, (ii) displaying data with hidden features, and (iii) visualizing relationships between the observed data (Yoshino & Hesary, 2014).

Cause and effect diagram. A cause and effect diagram (Ishikawa diagram) can classify the processes and parameters to be studied (Ishikawa, 1985; Simanovaa & Gejdosb, 2015). Key causal analysis can be applied to study the causes of a given event. The relative causes for a special task are divided into categories and presented in diagrams (Ishikawa, 1991; Dobrusskin, 2016). The main problems of business activities are classified into six classic categories: people, management, processes, environment, materials, and equipment (Ishikawa, 1986; Bose, 2012).

Data sample for case study

Definition of micro and small manufacturing industries. According to the Republic of Indonesia law number 20, 2008, micro and small manufacturing businesses are defined as follows (UURI, 2008):

- Micro manufacturing industries are productive business owned by an individual and/or individual business entity that has a net worth of IDR 50 million (excluding land and buildings) or annual sales of at most IDR 300 million.
- Small manufacturing industries are stand-alone productive economic enterprises owned by an individual or business entity that is neither a subsidiary nor branch, directly or indirectly, of a medium or large company that has a net worth of IDR 50-500 (excluding land and buildings) or annual sales of IDR 300 million–2.5 billion.

Industry classification according to KBLI. This study used the *Klasifikasi Baku Lapangan Usaha Indonesia (KBLI) rev. 4 Tahun 2009* classification of industries (BPS, 2014), as shown in Table 1. The industries were equated to DMUs for DEA analysis.

Input and output variables. We selected four types of input data – (i) number of establishments, (ii) number of workers, (iii) input cost, and (iv) labor cost – and two types of output data – (i) value of gross output and (ii) value added (at market price) – over a six-year period (2010-15), for a total 24 input variables and 12 output variables. The input and output variables are shown in Table 2.

The actual input and output data used for analyzing the micro and small manufacturing industries are shown in Tables 3-6.

Table 1. Classification of industries according to KBLI.

DMU	KBLI code	Industry classification
1	10	Food products
2	11	Beverages
3	12	Tobacco
4	13	Textiles
5	14	Wearing apparel
6	15	Leather
7	16	Wood, products made of wood (excluding furniture), and plaited materials
8	17	Paper and paper products
9	18	Printing and media reproduction
10	20	Chemistry and chemical products
11	21	Pharmacy, medical & traditional products
12	22	Rubber and plastic products
13	23	Non-metallic mineral products
14	24	Natural metals
15	25	Metal goods, non-metallic goods and equipment
16	26	Computers, electronics, and optical products
17	27	Electrical equipment
18	28	Machinery and equipment (excluding others)
19	29	Automotive, trailer, and semi-trailer
20	30	Other transport equipment
21	31	Furniture
22	32	Other manufacturing
23	33	Repair services and installation of machinery and equipment

Source: BPS, 2014.

Table 2. Input and output variables for the micro and small manufacturing industries 2010-15.

Input variable			Input variable		
Input type	**Variable**	**Explanation**	**Output type**	**Variable**	**Explanation**
Input 1	X1	Number of establishments in 2010	Output 1	X25	Value of gross output in 2010
	X2	Number of establishments in 2011		X26	Value of gross output in 2011
	X3	Number of establishments in 2012		X27	Value of gross output in 2012
	X4	Number of establishments in 2013		X28	Value of gross output in 2013
	X5	Number of establishments in 2014		X29	Value of gross output in 2014
	X6	Number of establishments in 2015		X30	Value of gross output in 2015
Input 2	X7	Number of workers in 2010	Output 2	X31	Value added in 2010
	X8	Number of workers in 2011		X32	Value added in 2011
	X9	Number of workers in 2012		X33	Value added in 2012
	X10	Number of workers in 2013		X34	Value added in 2013
	X11	Number of workers in 2014		X35	Value added in 2014
	X12	Number of workers in 2015		X36	Value added in 2015
Input 3	X13	Input cost in 2010			
	X14	Input cost in 2011			
	X15	Input cost in 2012			
	X16	Input cost in 2013			
	X17	Input cost in 2014			
	X18	Input cost in 2015			
Input 4	X19	Labour cost in 2010			
	X20	Labour cost in 2011			
	X21	Labour cost in 2012			
	X22	Labour cost in 2013			
	X23	Labour cost in 2014			
	X24	Labour cost in 2015			

Source: BPS, 2014.

Table 3. Actual input data for micro manufacturing industry 2010-15.

KBLI	X1	X2	X3	X4	X5	X6 →	X24
10	881,590	872,869	871,898	1,008,890	1,125,425	1,473,205	6,089,148
11	29,848	32,516	51,069	45,508	43,293	45,922	152,003
12	22,804	54,258	32,535	48,887	43,152	43,371	143,429
13	221,054	226,017	192,149	265,498	291,151	127,245	186,313
14	244,810	202,809	347,887	240,833	304,418	360,622	2,800,832
15	26,647	17,690	37,514	17,326	30,789	32,136	664,335
16	623,761	697,970	554,992	728,786	784,753	674,970	3,262,209
17	6,780	6,628	9,487	8,672	7,904	4,633	32,727
18	19,675	19,058	34,320	22,918	22,719	20,025	289,904
20	18,223	23,678	16,002	20,181	22,065	20,081	134,060
21	4,974	3,862	10,909	5,607	6,206	4,464	16,802
22	12,346	14,457	23,300	19,999	14,300	10,155	127,956
23	193,129	179,578	233,396	196,845	242,242	234,762	3,072,288
24	1,288	815	369	1,080	1,801	31,122	465,217
25	54,571	68,827	118,106	61,801	67,825	99,046	2,313,983
26	397	238	79	121	224	46	713
27	113	829	551	324	32	162	10,810
28	1,129	308	10,542	633	1,265	952	19,255
29	3,314	1,610	1,433	1,800	1,530	1,700	93,289
30	4,383	6,425	8,138	5,537	5,546	4,076	99,868
31	96,938	66,687	136,983	102,957	122,182	117,901	2,784,572
32	55,592	51,986	113,818	75,071	73,274	73,002	453,295
33	6,481	5,616	7,270	7,741	8,467	6,253	63,570

Source: BPS, 2014.

Table 4. Actual output data for micro manufacturing industry 2010-15.

KBLI	X25	X26	X27	X28	X29 →	X36
10	43,311,764	10,749,140	53,541,924	74,898,866	98,445,757	48,546,016
11	932,730	285,625	1,593,378	1,780,427	2,243,305	1,191,521
12	576,565	176,801	531,301	562,593	3,324,119	1,964,479
13	3,263,863	1,015,001	4,379,799	5,515,227	7,546,381	1,794,978
14	9,307,718	2,243,629	14,364,606	11,901,070	24,522,631	14,931,396
15	3,984,424	806,459	6,912,816	1,865,006	5,116,281	2,382,186
16	12,380,541	4,654,844	16,397,681	21,972,598	30,783,432	16,134,398
17	645,642	42,962	177,130	336,649	407,005	313,825
18	1,904,485	444,025	2,699,324	2,205,214	4,044,801	1,428,031
20	1,018,880	350,138	771,852	1,722,685	1,381,001	771,046
21	247,198	39,643	297,404	175,812	447,477	149,386

Table 4. Continued.

22	651,510	179,296	404,091	1,134,569	1,097,850	507,681
23	9,598,327	2,590,546	14,847,546	11,750,057	20,627,987	13,308,155
24	242,307	11,976	57,349	408,960	209,461	1,814,061
25	6,200,869	1,677,197	10,388,149	7,336,800	13,615,484	9,294,653
26	72,148	14,450	64,773	45,786	53,571	2,810
27	8,105	10,475	45,129	35,937	5,704	25,293
28	312,909	11,559	1,669,760	176,229	357,748	98,921
29	241,607	43,483	278,525	297,590	355,669	300,865
30	445,546	207,065	885,458	527,424	1,005,939	553,440
31	9,829,359	1,919,912	9,421,179	11,222,619	24,682,332	10,939,476
32	3,030,729	647,626	3,408,072	6,336,166	11,097,750	3,946,402
33	370,449	105,598	323,992	583,393	1,077,544	302,478

Source: BPS, 2014.

Table 5. Actual input data for small manufacturing industry 2010-15.

KBLI	X1	X2	X3	X4	X5	X6 →	X24
10	48,320	118,403	70,712	158,651	73,066	93,814	8,313,715
11	547	1,408	2,605	1,962	1,401	1,208	174,237
12	30,365	452	856	14,823	21,590	19,750	494,897
13	13,603	17,117	15,008	27,541	12,246	4,188	428,314
14	31,738	101,629	107,141	99,169	50,165	46,601	5,033,968
15	6,263	18,959	16,417	22,824	12,477	12,686	2,546,117
16	15,345	39,442	29,850	53,130	20,729	19,954	2,339,325
17	488	886	1,400	1,430	1,160	1,096	132,095
18	4,630	8,629	17,596	8,666	8,295	5,330	601,715
20	945	1,810	164	3,987	1,813	1,558	118,996
21	69	39	1	909	238	526	37,448
22	1,440	1,472	2,813	1,999	2,790	492	38,280
23	22,429	59,830	48,808	69,017	33,324	29,758	3,288,153
24	265	766	88	310	146	461	30,786
25	7,160	17,986	18,050	17,934	12,749	13,990	1,628,732
26	37	39	29	218	134	260	35,778
27	86	36	725	291	220	54	15,362
28	411	514	686	1,178	394	258	32,495
29	174	1,195	524	1,449	2,042	666	112,005
30	325	786	610	839	903	972	72,021
31	10,228	22,307	46,226	30,874	19,475	20,699	3,251,407
32	7,306	9,459	23,884	13,723	9,031	8,123	975,477
33	703	1,120	1,103	427	113	578	68,570

Source: BPS, 2014.

Table 6. Actual output data for small manufacturing industry 2010-15.

KBLI	X25	X26	X27	X28	X29	→ X36
10	18,006,444	15,218,125	39,647,367	119,804,252	76,113,294	111,683,820
11	148,210	127,855	1,084,130	920,346	300,550	1,477,254
12	3,915,019	14,098	2,061,137	4,913,431	25,687,349	5,470,456
13	8,627,661	1,913,227	9,964,374	14,174,495	7,508,771	2,674,862
14	18,462,385	17,155,637	37,590,051	70,919,284	45,262,419	36,453,033
15	2,840,061	3,848,647	5,336,472	13,903,014	11,762,876	12,763,885
16	5,610,725	5,375,054	10,360,611	26,792,541	15,096,114	20,018,114
17	158,029	91,779	2,734,429	493,621	513,884	845,861
18	1,884,087	970,774	4,482,054	4,582,127	5,217,626	5,798,059
20	603,329	147,179	62,847	4,567,768	1,645,774	1,209,636
21	6,187	2,810	52	633,301	71,748	273,293
22	546,633	286,366	2,376,151	1,250,157	2,725,178	219,411
23	4,360,140	3,193,028	14,870,478	20,634,809	12,941,545	13,654,825
24	151,853	77,964	21,250	107,934	145,884	102,070
25	6,742,643	2,646,080	7,660,634	14,551,120	10,742,431	11,018,962
26	47,615	7,235	38,061	118,980	77,330	174,586
27	36,900	4,653	522,834	2,455,478	286,531	53,405
28	293,382	53,379	1,528,909	920,167	2,460,102	186,754
29	111,050	114,288	204,580	1,394,388	1,383,319	571,964
30	240,787	169,655	220,176	455,591	2,635,217	511,610
31	4,815,720	2,599,050	20,248,556	17,534,338	27,719,270	22,474,312
32	1,394,911	756,693	13,175,299	5,473,502	10,538,755	11,187,066
33	132,409	94,153	319,748	506,010	24,757	425,813

Source: BPS, 2014.

Analysis

This study evaluated the performance of the micro and small manufacturing industries (MSMI) in Indonesia using a combination of factor analysis to select the input and output variables and performance evaluation.

Factor analysis for input and output variable selection. This study used SPSS to conduct the principal component analysis (PCA). Factor analysis was applied to reduce the data to eliminate highly correlated variables. The principal component method of extraction started by determining the linear combination of variables or components that counted for the greatest variation in the original variables. Next, PCA determined the other components that accounted for the greatest remaining variation that were uncorrelated with the previous components. This continued until the number of components equaled the number of original variables.

Performance evaluation uses DEA method. An input-oriented DEA envelopment model was used to obtain an optimal solution using Microsoft Excel and Solver software. Based on the optimal solution for the efficiency score, the causative factors of efficient and inefficient DMU-KBLI were then determined by applying a cause and effect diagram to analyze marketing, human resources, materials, machinery, capital and finance, product, technology, support, research & development, distribution, promotion, competitors, and policy variables.

RESULTS

Factor analysis for input and output variable selection

Input variable selection. The communalities of each variable exceeded 78%. Total variance-explained had initial eigenvalues greater than 1 for the extracted components 1 and 2. Based on the initial eigenvalues for the variance-explained, the value of summary percentage variance for the micro manufacturing industry (MMI) was equal to 97% and the small manufacturing industry (SMI) was equal to 95%. The values indicated that these two extracted components explained nearly 97% and 95% of the variability in the original 24 input variables for MMI and SMI, respectively. Therefore, we can considerably reduce the complexity of the data set by using these components, with only 3% loss of information for MMI and 5% loss of information for SMI. Table 7 describes the results of total variance-explained.

The *component matrix* extracted two components, namely, components 1 and 2. It showed the correlations between the independent variables and these two extracted components. The correlation value between the variables and selected components was greater than 0.1. This indicated that the input selected variables for MMI were X6, X12, X16, and X20; and for SMI were X3, X9, X18, and X21.

Table 7. Total variance-explained.

Type of industry	Component	Initial eigenvalues			Extraction sums of squared loadings		
		Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
MMI	1	22.04	91.83	91.83	22.04	91.83	91.83
	2	1.24	5.15	**96.99**	1.24	5.15	**96.99**
	3	0.59	2.44	99.43			
	4	0.05	0.22	99.65			
	↓	↓	↓	↓			
	24	0.00	0.00	100.00			
SMI	1	21.42	89.24	89.24	21.42	89.24	89.24
	2	1.32	5.49	**94.73**	1.32	5.49	**94.73**
	3	0.59	2.47	97.20			
	4	0.28	1.16	98.36			
	↓	↓	↓	↓			
	24	0.00	0.00	100.00			

Source: BPS, 2014.

Output variable selection. The communalities of each variable exceeded 87%. Total variance explained had initial eigenvalues greater than 1. The extracted component formed in this study consisted of only one component, namely, component 1. Based on the initial eigenvalues of the variance explained, the value of percentage variance for the factors explains 98% of the value of the variables in the micro manufacturing industry and 92% in the small manufacturing industry. Only one component was extracted from the rotated component matrix result, indicating that the solution could not be rotated. The correlation value between the variables and components selected in the component score coefficient matrix was greater than 0.08, indicating that the output selected variables were X30 and X36 for MMI and X28 and X34 for SMI.

Performance evaluation

Factor analysis yielded four input and two output selected variables for each industry type: (a) Micro manufacturing industry (MMI) – input1 (X6)-number of establishments, input2 (X12)-number of workers, input3 (X16)-input cost, input4 (X20)-labor cost, output1 (X12)-value of gross output, and output2 (X12)-value added; and (b) Small manufacturing industry (SMI) – input1 (X3)-number of establishments, input2 (X9)-number of workers, input3 (X18)-input cost, input4 (X21)-labor cost, output1 (X28)-value of gross output, and output2 (X34)-value added.

Table 8 shows the efficiency values of MMI and SMI (DMU-KBLI) based on the selected input and output variables. Values over 0.8 were considered efficient.

The PCA- and DEA-based estimates demonstrated that it was possible to classify the DMUs into eight categories: efficient MMI, inefficient MMI, efficient SMI, inefficient SMI, efficient MMI – efficient SMI, inefficient MMI – inefficient SMI, efficient MMI – inefficient SMI, and efficient SMI – inefficient MMI. The DMU-KBLI classification and its percentage composition for each type of manufacturing industry are shown in Table 9.

To improve the DMU-KBLI activities identified as inefficient requires reducing the input variables; the reduction amount can be found from the values of the weak input variables in Table 10.

Table 8. Efficiency and inefficiency values of MMI and SMI based on the selected input and output variables.

DMU	KBLI	Micro manufacturing industry (MMI)		Small manufacturing industry (SMI)	
		Efficiency value	**Explanation**	**Efficiency value**	**Explanation**
1	10	1	Efficient	1	Efficient
2	11	1	Efficient	0.52	Inefficient
3	12	1	Efficient	0.80	Inefficient
4	13	0.49	Inefficient	0.33	Inefficient
5	14	1	Efficient	1	Efficient
6	15	1	Efficient	1	Efficient
7	16	0.81	Efficient	0.81	Efficient
8	17	1	Efficient	0.99	Efficient
9	18	1	Efficient	0.70	Inefficient
10	20	0.66	Inefficient	0.66	Inefficient
11	21	0.53	Inefficient	0.55	Inefficient
12	22	0.74	Inefficient	0.74	Inefficient
13	23	1	Efficient	1	Efficient
14	24	1	Efficient	1	Efficient
15	25	1	Efficient	1	Efficient
16	26	0.76	Inefficient	1	Efficient
17	27	1	Efficient	1	Efficient
18	28	1	Efficient	1	Efficient
19	29	1	Efficient	1	Efficient
20	30	1	Efficient	1	Efficient
21	31	1	Efficient	1	Efficient
22	32	1	Efficient	1	Efficient
23	33	1	Efficient	0.61	Inefficient

Table 9. DMU-KBLI classification of MSMI and its percentage composition.

Type of manufacturing industry	DMU-KBLI classification	Percentage composition	DMU-KBLI & efficiency value
MMI	Efficient MMI	78%	DMU1-KBLI10(1), DMU2-KBLI11(1), DMU3-KBLI12(1), DMU5-KBLI14(1), DMU6-KBLI15(1), DMU7-KBLI16(0.81), DMU8-KBLI17(1), DMU9-KBLI18(1), DMU13-KBLI23(1), DMU14-KBLI24(1), DMU15-KBLI25(1), DMU17-KBLI27(1), DMU18-KBLI28(1), DMU19-KBLI29(1), DMU20-KBLI30(1), DMU21-KBLI31(1), DMU22-KBLI32(1) and DMU23-KBLI33(1).
	Inefficient MMI	22%	DMU4-KBLI13 (0.49), DMU10-KBLI20 (0.66), DMU11-KBLI21 (0.53), DMU12- KBLI22 (0.74) and DMU16-KBLI26 (0.76).
SMI	Efficient SMI	65%	DMU1-KBLI10(1), DMU5-KBLI14(1), DMU6-KBLI15(1), DMU7-KBLI16(0.81), DMU8-KBLI17(0.99), DMU13-KBLI23(1), DMU14-KBLI24(1), DMU15-KBLI25(1), DMU16-KBLI26(1), DMU17-KBLI27(1), DMU18-KBLI28(1), DMU19-KBLI29(1), DMU20-KBLI30(1), DMU21-KBLI31(1) and DMU22-KBLI32(1).
	Inefficient SMI	35%	DMU2-KBLI1 (0.52), DMU3-KBLI12 (0.79), DMU4-KBLI13 (0.33), DMU9-KBLI18 (0.69), DMU10-KBLI20 (0.66), DMU11-KBLI21 (0.55), DMU12-KBLI22 (0.74) and DMU23-KBLI33 (0.61).
MMI-SMI	Efficient MMI-SMI	61%	DMU-KBLI of efficient MMI-SMI are as follow: DMU1-KBLI10 (1;1), DMU5-KBLI14 (1;1), DMU6-KBLI115 (1;1), DMU7-KBLI16 (0.81; 0.81), DMU8-KBLI17 (1; 0.99), DMU13-KBLI23 (1;1), DMU14-KBLI24 (1;1), DMU15-KBLI25 (1;1), DMU17-KBLI27 (1;1), DMU18-KBLI28 (1;1), DMU19-KBLI29 (1;1), DMU20-KBLI30 (1;1), DMU21-KBLI32 (1;1) and DMU22-KBLI32 (1;1).

Table 9. Continued.

Type of manufacturing industry	DMU-KBLI classification	Percentage composition	DMU-KBLI & efficiency value
	Inefficient MMI-SMI	17%	DMU4-KBLI13 (0.49; 0.33), DMU10-KBLI20 (0.66; 0.66), DMU11-KBLI21 (0.53; 0.55) and DMU12-KBLI22 (0.74; 0.74).
	Efficient MMI-Inefficient SMI	17%	DMU2-KBLI11 (1; 0.52), DMU3-KB LI12 (1; 0.80), DMU9-KBLI18 (1; 0.69) and DMU23-KBLI33 (1; 0.61).
	Efficient SMI-Inefficient MMI	5%	DMU16-KBLI26 (0.76; 1).

Table 10. Values of the weak input variables for the micro and small manufacturing industry (MSMI).

Type of manufacturing industry	DMU-KBLI	Weak input variables			
		(X6)	(X12)	(X16)	(X20)
Micro manufacturing industry	DMU4-KBLI13	22,548	0	548,139	0
	DMU10-KBLI 20	0	6,770	621,752	0
	DMU11-KBLI 21	873	0	0	0
	DMU12-KBLI 22	1,809	0	457,974	0
	DMU16-KBLI 26	0	0	0	0
		(X3)	(X9)	(X18)	(X21)
Small manufacturing industry	DMU2-KBLI11	6,267	0	117,335	0
	DMU3-KBLI12	0	25,641	0	0
	DMU4-KBLI13	15,285	0	367,722	0
	DMU9-KBLI18	0	879	0	0
	DMU10-KBLI20	0	4,899	338,019	0
	DMU11-KBLI21	434	0	0	0
	DMU12-KBLI22	1,337	0	248,391	0
	DMU23-KBLI33	1,330	0	0	539

DISCUSSION

Our study used PCA to select the input and output variables based on the same concept found in Zhu (1998), Adler and Yazhemsky (2010), and Yoshino and Hesary (2014), applying this to evaluate the performance of the micro and small manufacturing industries in Indonesia. We compared the rotated component and component score coefficient matrices to select the variables with the greatest values. In the absence of a conventional rule, a dilemma arose in selecting the variables if they had the same value.

We used a similar DEA approach as Cook and Zhu (2008) in Equation (1) to transform the inefficient DMU-KBLI activities into efficient ones. However, we differed on the calculation of weak input variables. Using their approach, we defined the values of the weak input variables X6, X12, X16, and X20 for DMU10-KBLI20, DMU11-KBLI21, DMU12-KBLI22, and DMU16-KB LI26 in micro manufacturing industry (MMI) as 0.

We had to overcome the limitations of the Cook and Zhu approach, improving the weak input variables and minimizing the number of input variables. The values were as follows: DMU10-KBLI 20 (X12 = 6,770; X16 = 621,752), DMU11-KBLI 21 (X6 = 873), and DMU12-KBLI 22 (X6 = 1,809; X16 = 457,974).

To improve the efficiency of DMU-KBLI activities, causative factors must be considered; the common factors are listed in Tables 11 and 12. Based on our results, we determined that the following factors were causative for MSMI in Indonesia: marketing, human resources, materials, machinery, capital and finance, product, technology, support, research & development, distribution, promotion, competitors, and policy. The information presented in these tables can be used as the benchmark to determine the internal factors (strengths and weaknesses) and external factors (opportunities and threats) of MSMI businesses and in order to further develop them.

Table 11. Causative factors of effective DMU-KBLI.

No	Aspect	Description
1	Marketing	Sensitivity to the requirements of the market, aimed marketing possibilities, and benchmarking conducted to define market conditions.
2	Human resources	Existence of human resources and the necessary qualifications and experience of these resources.
3	Materials	Presence of raw materials, strong links with suppliers, and the right choice of suppliers of raw materials.
4	Machinery	Machinery and production facilities that correspond to existing standard operations.
5	Capital & finance	Availability of operating capital, possibility to get bank credits. and the financial ability to buy products and services.

Table 11. Continued.

No	Aspect	Description
6	Product	Quality of goods, level of export goods, flexible prices of goods (bargaining), the existence of price discounts, export opportunities, possessing good links with customers, and the existence of competitors.
7	Technology	Management systems of information monitoring demonstrate the increasing sophistication and presence of advanced technology.
8	Support	Role of government and private structures, rapid population growth, the existence and influence of non-government organizations (NGOs).
9	Research & development	The existence of well-developed educational and training systems; the presence of research and development structures.

Table 12. Causative factors of ineffective DMU-KBLI.

No	Aspect	Description
1	Marketing	Poor marketing strategies, sales levels that fall short of market requirements.
2	Human resources	Human resources with insufficient education or training.
3	Materials	Poor quality of raw materials, restrictions in the purchase of raw materials, increasing costs of raw materials, and decreasing supply of or access to raw materials.
4	Machinery	Manufacturing process based on old technology and the lack of processing facilities and equipment.
5	Capital & finance	Capital resource limitations and poor financial management.
6	Product	High costs of goods and service, customer complaints, low price requirements of customers, and the need for good quality products at competitive prices.
7	Technology	Absence of innovation or slow to innovate.
8	Distribution	Limited distribution networks.
9	Promotion	Insufficient promotions.
10	Competitors	Arrival of numerous new competitors, strong competition, rapidly innovating competitors.
11	Policy	Currency risks, inflationary risks, country economic risks, government politics directed to reducing public subsidies, unstable and dangerous domestic political situation.

The estimations using PCA and DEA methods in this study demonstrated that it is possible to newly classify DMU groups, and offers potential for improving DMU efficiency. The results of this study can also be used by the government as a base to formulate development strategies for MSMI in Indonesia.

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REFERENCES

Adler, N., & Yazhemsky, E. (2010). Improving discrimination in data envelopment analysis: PCA–DEA or variable reduction. *European Journal of Operational Research, 202*, 273–284. https://doi.org/10.1016/j.ejor.2009.03.050

Bose, T.K. (2012). Application of fishbone analysis for evaluating supply chain and business process- A case study on the St. James Hospital. *International Journal of Managing Value and Supply Chains (IJMVSC), 3*(2), 17-24. https://doi.org/10.5121/ijmvsc.2012.3202

BPS. (2014). Profile of micro and small industry in 2014 (*Profil industri mikro dan kecil tahun 2014*), Katalog BPS 6104006, BadanPusatStatistik, Jakarta, Indonesia.

Charnes, A., Cooper, W.W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research, 2*(6), 429–444. https://doi.org/10.1016/0377-2217(78)90138-8

Cook, W.D., & Zhu, J. (2008). *Data envelopment analysis: Modeling operational processes and measuring productivity*. CreateSpace Independent Publishing Platform.

Cooper, W.W., Seiford, L.M., & Tone, K. (2007). *Introduction to data envelopment analysis and its uses with DEA-solver software and references, 2nd ed.*, Springer, U.S.A.

Dobrusskin, C. (2016). On the identification of contradictions using cause effect chain analysis. *Procedia CIRP 39*, 221–224. https://doi.org/10.1016/j.procir.2016.01.192

Ishikawa, K. (1985). *What is total quality control? The Japanese way (1 ed.)*. Englewood Cliffs, New Jersey: Prentice-Hall.

______. (1986). *Guide to quality control.* Tokyo, Japan: Asian Productivity Organization.

______. (1991). *Guide to quality control.* Tokyo, Japan: Asian Productivity Organization.

Paradi, J.C., Vela, S., & Yang, Z.J. (2004). Assessing bank and bank branch performance. In: Cooper W.W., Seiford L.M., Zhu J. (eds) *Handbook on Data Envelopment Analysis*. International Series in Operations Research & Management Science, vol. 71. Springer, Boston, MA.

Putri, E.P. (2016b). Cluster development of small and medium manufacturing industry in Surabaya City, East Java, Indonesia. In Ivan A. Parinov, Shun-Hsyung Chang, Vitaly Yu. Topolov (Eds.). *Proceedings of the 2015 International Conference on Physics and Mechanics of New Materials and Their Applications, devoted to 100-th Anniversary of the Southern Federal University*. (pp. 565-570). Nova Science Publishers, New York.

Putri, E.P., & Abdulrahim M. (2017a). Business development of small and medium enterprises as poverty alleviation efforts in East Java province, Indonesia. In Ivan A. Parinov, Shun-Hsyung Chang, Muaffaq A. Jani (Eds.). *Proceedings of the 2016 International Conference on Physics and Mechanics of New Materials and Their Applications*. (pp. 627-633.) Nova Science Publishers, New York.

Putri, E.P., Chetchotsak, D., Jani, M.A., & Hastijanti, R. (2017b). Performance evaluation of micro and small manufacturing industry in Indonesia. *Proceedings of International Conference on Simulation and Modelling (SIMMOD 2017)* (pp. 82-92).

Putri, E.P., Chetchotsak, D., Ruangchoenghum, P., Jani, M.A., & Hastijanti, R. (2016a). Performance evaluation of large and medium scale manufacturing industry clusters in East Java Province Indonesia. *International Journal of Technology, 7*, 1117-1127. https://doi.org/10.14716/ijtech.v7i7.5229

Simanovaa, L., & Gejdosb, P. (2015). The use of statistical quality control tools to quality improving in the furniture business. *Procedia Economics and Finance, 34*, 276 – 283.

Tolooa, M., & Babaeeb, S. (2015). On variable reductions in data envelopment analysis with an illustrative application to a gas company. *Applied Mathematics and Computation, 270*, 527–533. https://doi.org/10.1016/j.amc.2015.06.122

UURI. (2008). The law of the Republic of Indonesia number 20 year 2008 (*Undang-Undang Republik Indonesia Nomor 20 Tahun 2008 tentang Usaha Mikro, Kecil dan Menengah*).

Yuzhi, S., & Zhangna. (2012). Study of the input-output overall performance evaluation of electricity distribution based on DEA method. International Conference on Future Energy, Environment, and Materials. *Energy Procedia, 16*, 1517 – 1525. https://doi.org/10.1016/j.egypro.2012.01.238

Yoshino, N., & Hesary, F.T. (2014). Analytical framework on credit risks for financing SMEs in Asia. *Asia-Pacific Development Journal, 21*(2), 1–21.

Zhu, J. (1998). Data envelopment analysis vs. principal component analysis. *European Journal of Operational Research, 111*, 50–61. https://doi.org/10.1016/S0377-2217(97)00321-4