A DATA ENVELOPMENT ANALYSIS APPROACH TO ASSESS TECHNICAL EFFICIENCY OF LARGE AND MEDIUM MANUFACTURING INDUSTRY IN CENTRAL JAVA PROVINCE, INDONESIA

M. Mujiya Ulkhaq¹ and Trisna Nagris Pratiwi²

¹(Diponegoro University, Semarang)
²(Master of Management Study Program, Sebelas Maret University, Surakarta)

*) Corresponding e-mail: ulkhaq@live.undip.ac.id

Abstract

several studies. However, there is limited study conducted in large and medium manufacturing industries context. This study, therefore, aims to analyse the technical efficiency of the large and medium manufacturing industries in Central Java Province, Indonesia. Understanding the technical efficiency is important as firms with full technical efficiency, the less inputs
they use, the larger output they achieve. Data envelopment analysis with output-oriented and variable returns-to-scale is used to accomplish the objective of this study. The output is measured by total output value, while the inputs are cost of labour, raw materials, other materials, fuel, electricity, and fixed capital. Result shows that among twenty-four decision-making units under-investigated, six of them are considered as the most efficient.

**Keywords:** Central Java Province, data envelopment analysis, Indonesia, industry, large and medium manufacturing

**Citation:**

**INTRODUCTION**

The manufacturing industry contributed the most to Indonesia’s 7.07% economic growth in the second quarter of 2021, with a 6.91% growth despite pressure from the COVID-19 pandemic. According to the data from the Ministry of Industry, the manufacturing sector contributed the largest to the national gross domestic product (GDP) in the second quarter of 2021, amounting to 17.34%.

In the third quarter of 2021, the manufacturing industry grew 3.68% and contributed 0.75% to the national economy’s growth. The proven resiliency indicates that the trajectory of industrial growth is still on track, and the sector is set to become the driver for the national economy, aiming for a GDP contribution of more than 20% by 2024.

Statistics Indonesia classifies manufacturing industry into four classes based on its scale. They are large (number of labours is more than 100), medium (number of labours is between 20 to 99), small (number of labours is between 5 to 19), and micro or domestic industries (number of labours is less than 5).
In the first quarter of 2019, the production of large and medium manufacturing industries rose 4.45% compared to the same period last year. This number is also higher than in the average of 2018 which was only 4.07%. The increase in the production was supported by the apparel industry sector, which rose 29.19% due to the abundance of demands, especially from the export market.

From the entire manufacturing sectors value-added, more than 40% is contributed by large and medium manufacturing industries. By contrast, small and micro manufacturing industries in the same period contributed less than 10% on average.

Despite the important role of large and medium manufacturing industries in Indonesia’s economy, this sector has experienced inconsistent growth in both output growth and labour productivity growth (Primanthi, 2021). The output growth fluctuated from minus 10% to 13% during 2000-2015. The instability of output growth can be analysed by measuring the source of output growth, either due to technological factors or input formation (Hulten, 2001).

The objective of this study is then to analyse the technical efficiency of large and medium manufacturing industries in Indonesia. Understanding the technical efficiency, which is simply defined as the ratio of output to input (Cooper et al., 2006), is important because if firms perform consistently with full technical efficiency, the less inputs they use, the larger output they achieve.

Technical efficiency in Indonesian manufacturing industry has been measure in several studies. However, there is limited study in measuring the technical efficiency of large and medium manufacturing industries context (see subsequent section). Therefore, this study seeks to fill the gap in the literature by assessing the technical efficiency of large and medium manufacturing industries in Central Java Province, Indonesia.

The rest of the paper is structured as follows. The following section shows literature review we conduct to show the novelty of this study. The next section presents the data used in this study, including inputs and output. The fourth section describes the empirical model of this study, i.e., output-oriented DEA with VRS approach. The five section shows the result of this study while the last section concludes.
LITERATURE REVIEW

Technical efficiency is mainly assessed by frontier methods, which can be categorized as parametric and non-parametric approach. The difference lies in the fact that in the parametric approach, one has to define a functional form a priori and estimates the finite set of unknown parameters from the data. On the other hand, the non-parametric approach is considered simple, easy to handle multiple outputs, and it does not require any assumption about the functional form. Among the non-parametric approach, DEA is the most popular tool in assessing technical efficiency.

Literature about assessing technical efficiency of manufacturing industry in Indonesia using DEA is quite limited. We then conduct a search in the Scopus database (www.scopus.com) to verify this claim. The following query is used: TITLE-ABS-KEY(manufactur* AND industry AND efficien* AND Indonesia* AND (dea OR “data envelopment analysis”))¹. It means that the articles which contains this query in the title, abstract, or keywords are extracted.

The period of time is not limited. For the sake of quality assurance, the article type is restricted to peer-reviewed research article published in a journal as these sources are the most useful for literature reviews (Saunders et al., 2012). Therefore, other types of articles such as books or book chapters, conference proceedings, short communications, letters, or editorial materials are excluded. From a pragmatic point of view, only articles published in English are included.

The search yields 6 (six) articles. This low yield indicates that this research area is under-studied—especially among scholars in Indonesia, confirming our previous claim. However, among those six extracted articles, we cannot find the full text of Saputra (2011) so that this article is excluded for further analysis. These extracted articles are discussed as follows.

Sulistyawati and Suryani (2022) used DEA to assess technical efficiency of 130 public manufacturing firms listed in the Indonesian Stock Exchange in 2019. Setiawan and Sule (2020) investigated technical efficiency of Indonesian state-owned enterprises manufacturing industry. They used two-stage DEA; as the first stage-

¹ The asterisk sign (*) is used to find a root word plus all the words made by adding letters to the end (or beginning) of it.
was intended to calculate the technical efficiency, while at the second stage aimed to investigate the effects of determinants of efficiency.

Setiawan et al. (2019) assessed technical efficiency of Indonesian micro and small enterprises. They used the data from the micro and small industry survey sourced from Statistics Indonesia for the period 2010–2015. The technical efficiency was estimated using DEA with bootstrapping approach. Van Dijk and Szirmai (2011) analysed the micro-dynamics of catch-up in Indonesian paper manufacturing using a two-country plant-level dataset for the period 1975–1997. They applied DEA to measure to what extent Indonesian paper mills are catching up with Finnish mills in terms of technical efficiency. Finally, Halim (2010) evaluated technical efficiency and marketing productivity of Indonesian public manufacturing firms listed at the Indonesia Stock Exchange during the period 2001–2007.

From the literature review, it is apparent that no research has been conducted to—especially—investigate technical efficiency of large and medium manufacturing industries. Therefore, this study seeks to fill the gap in the literature. In addition, this study is expected to provide a portrait of large and medium manufacturing industries in Indonesia, given the role of this industry in Indonesian economy. The manufacturing sector has contributed 27% on average to Indonesia’s GDP between 2000 and 2015, with more than 40% of its value-added contributed by large and medium scale (Primanthi, 2021).

DATA AND VARIABLES

This study uses data from the annual survey held by Statistics Indonesia of Central Java Province for the period of 2019. The large and medium manufacturing sector is divided into 24 different industrial classifications following the International Standard Industrial Classification of all Economic Activities (ISIC) Revision 4. Statistics Indonesia defines the medium and large industries as the firms with number of labors of 20 to 99 labors and number of labors of more than 100, respectively.

Output in this study is measured by total output value in thousand rupiahs (O) comprises of: (i) value of goods produced from production process, (ii) value of electricity generated by the firm and some of it is sold to other parties, (iii) value of industrial services rendered (meaning that the materials are provided by other parties, while the firm only-
performs the processing process in exchange for a certain amount of money or goods as compensation), (iv) increase in stock of semi-finished products (it is the difference in the value of the stock of semi-finished products at the end of the year which is reduced by the stock at the beginning of the year), and (v) receipt from non-industrial services rendered. In the literature of efficiency measurement of manufacturing industries, total output value is commonly used, e.g., (Esquivias and Harianto, 2020; Margono and Sharma, 2006; Sugiharti et al., 2017).

We used six inputs in this study. The first is labour cost (L), representing the total expenditure incurred by employers for the employment of employees, including direct and indirect labour costs. Next are cost of raw materials (R) and cost of other materials (M), representing costs of materials used to manufacture a product. The next if cost of fuels, (F) e.g., gasoline, diesel, kerosene, coal used during the production process. The next if cost of electricity (E). The last is fixed capital cost (C), such as building, machinery, and equipment.

Those inputs are also commonly used in the study of efficiency measurement of manufacturing industries. Labour cost was used in Esquivias and Harianto (2020) and Sugiharti et al. (2017); material cost was used in Setiawan and Sule (2020), Setiawan et al. (2019), Esquivias and Harianto (2020), Margono and Sharma (2006), Ikhsan (2007); energy cost was used in Esquivias and Harianto (2020), Ikhsan (2007); and fixed capital cost was used in Setiawan and Sule (2020), Setiawan et al. (2019), Esquivias and Harianto (2020), Margono and Sharma (2006), Ikhsan (2007). The data is shown in Appendix I.

In DEA, the influence of inputs on output cannot be investigate; thus, the selection of inputs only depends on the literature without knowing whether the selected inputs significantly influence the output. However, Ferrera et al. (2010, 2011) argued that inputs must fulfill the requirement of isotonicity (i.e., ceteris paribus, more input implies an equal or higher level of output); hence, the selected inputs should present a significant positive correlation with the output in addition to have theoretical support from previous work.

In Table 1, we provide correlation coefficients of all variables used. Notice that in Table 1, the total output value is moderately and strongly correlated with inputs. For instance, the correlation between total output value and cost of raw materials is strong (0.912), while with the cost of labour is moderate (0.530).
Table 1. Correlation coefficients

<table>
<thead>
<tr>
<th>L</th>
<th>R</th>
<th>F</th>
<th>M</th>
<th>E</th>
<th>C</th>
<th>O</th>
</tr>
</thead>
<tbody>
<tr>
<td>L</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R</td>
<td>0.314</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>F</td>
<td>0.235</td>
<td>0.609</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>M</td>
<td>0.273</td>
<td>0.558</td>
<td>0.972</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>E</td>
<td>0.348</td>
<td>0.345</td>
<td>0.651</td>
<td>0.649</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>C</td>
<td>0.409</td>
<td>0.398</td>
<td>0.702</td>
<td>0.666</td>
<td>0.327</td>
<td>1</td>
</tr>
<tr>
<td>O</td>
<td>0.530</td>
<td>0.912</td>
<td>0.582</td>
<td>0.568</td>
<td>0.334</td>
<td>0.416</td>
</tr>
</tbody>
</table>

**EMPIRICAL MODEL**

Technical efficiency refers to the ability of a decision-making unit (DMU), in this study, it is large and medium manufacturing industry in Central Java Province, Indonesia, to minimize input used in the production of a given output, or the ability to obtain maximum output from a given inputs (Kumbhakar and Lovell, 2003). Consequently, a DMU is fully technically efficient if it produces the maximum possible output from a fixed level of inputs (in an output orientation), or if it uses the minimum possible inputs to produce a given level of output (in input orientation).

This study uses DEA to assess the technical efficiency. It is a non-parametric approach that requires very few assumptions in estimating technical efficiency compared to the parametric approach such as the stochastic frontier analysis (SFA). In SFA, one has to define a functional form a priori and estimate the finite set of unknown parameters from the data. In addition, due to the use of maximum likelihood method, the distribution of inefficiency must be defined a priori. In DEA, we do not consider those issues.

In estimating technical efficiency, DEA projects the inefficient DMU to the efficient DMU in the frontier. In doing that, DEA takes the most efficient DMU as the benchmark or frontier; and hence, inefficiency is regarded as deviation from the frontier. Let M be the number of inputs and N be the number of DMUs, (in this study, N = 24 and M = 6). Technical efficiency can be estimated by solving the mathematical linear programming as follows:
A Data Envelopment Analysis Approach to Assess Technical Efficiency of Large and Medium Manufacturing Industry in Central Java Province, Indonesia.

$$\max_{\lambda, \phi} \phi,$$

Subject to

$$X\lambda \leq x_o,$$

$$\phi y_o - Y\lambda \leq 0,$$

$$I\lambda = 1,$$

$$\lambda \geq 0,$$

(1)

Where $\phi \geq 1$ describes the output enlargement rate; it is stated as the proportional increase in output that could be achieved by the $i$th DMU given the same input quantities. $X$ represents the $M \times N$ input matrix, $Y$ is the $1 \times N$ input vector (in this study, we use single output), $\lambda$ is $N \times 1$ vector of constants, and $I$ is $1 \times N$ vector of ones. Efficiency $\theta$ is given as $\theta = 1/\phi$.

We use the output-oriented model of DEA, where it attempts to maximize output while using a given number of inputs. This assumption is appropriate to the condition of the Indonesian economy (Setiawan et al., 2012, 2019). In addition, we use the assumption of variable returns-to-scale, as this assumption is relevant to be applied in the Indonesian economy which is characterized by many distortions (Setiawan et al., 2019). According to these assumptions, if an optimal solution ($\theta^*, \lambda^*, s^-, s^+$) obtained satisfied $\theta^* = 1$ and has no slack ($s^- = 0, s^+ = 0$), then the DMUo is called VRS-efficient, otherwise, it is VRS-inefficient.

RESULT

The result of this study is shown in Table 2. Note that we use ISIC code as the DMU name, for instance, DMU 10 is the food manufacturing industry, DMU 31 contains firms in the furniture sector, etc. The efficiency score is depicted in the second column. According to output-oriented VRS-DEA, the most efficient manufacturing sectors are tobacco products (ISIC code: 12); coke, refined petroleum products (19); other non-metallic mineral products (23); electrical equipment (27); motor vehicles, trailers, and semi-trailers (29); and repair and installation of machinery and equipment (33) as these sectors have efficiency score of one. The other sectors are considered as inefficient since their efficiency scores are less than one.

Table 2 also shows the benchmark (reference set) with its corresponding $\lambda^*$. For instance, the $\lambda^*$s of DMU 10 are 0.72 and 0.28, showing the proportions contributed by DMU 12 and DMU 19 to the-
point used to evaluate DMU 10; hence, DMU 10 is technically inefficient. In fact, based on this reference set and λ*, we can express the input and output values needed to bring DMU 10 into efficient state as 0.832

Inputs of DMU 10 = 0.72 □ Inputs of DMU 12 + 0.28 □ Inputs of DMU 19, where 0.832, 0.72, and 0.28 are the efficiency score of DMU 10, λ* of DMU 10 for DMU 12, and λ* of DMU 10 for DMU 19, respectively. We can also observe from the magnitude of λ* that DMU 10 has more similarity to DMU 12 than DMU 19.

Table 2. DEA result

<table>
<thead>
<tr>
<th>DMU (ISIC, Rev. 4)</th>
<th>Efficiency score</th>
<th>Benchmark (λ*)</th>
<th>DMU (ISIC, Rev. 4)</th>
<th>Efficiency score</th>
<th>Benchmark (λ*)</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>0.832</td>
<td>12 (0.720078); 19 (0.279922)</td>
<td>22</td>
<td>0.492</td>
<td>12 (0.321135); 29 (0.215922); 33 (0.462943)</td>
</tr>
<tr>
<td>11</td>
<td>0.718</td>
<td>12 (0.052280); 19 (0.002942); 23 (0.023926); 33 (0.920853)</td>
<td>23</td>
<td>1.000</td>
<td>23 (1.000000)</td>
</tr>
<tr>
<td>12</td>
<td>1.000</td>
<td>12 (1.000000)</td>
<td>24</td>
<td>0.515</td>
<td>12 (0.074175); 19 (0.004829); 23 (0.001094); 33 (0.875439)</td>
</tr>
<tr>
<td>13</td>
<td>0.611</td>
<td>12 (1.000000)</td>
<td>25</td>
<td>0.531</td>
<td>12 (0.032736); 29 (0.091825); 33 (0.366932)</td>
</tr>
<tr>
<td>14</td>
<td>0.972</td>
<td>12 (0.520983); 29 (0.479017)</td>
<td>26</td>
<td>0.678</td>
<td>12 (0.022605); 27 (0.610463); 33 (0.366932)</td>
</tr>
<tr>
<td>15</td>
<td>0.974</td>
<td>12 (0.094277); 29 (0.449303); 33 (0.456420)</td>
<td>27</td>
<td>1.000</td>
<td>27 (1.000000)</td>
</tr>
<tr>
<td>16</td>
<td>0.566</td>
<td>12 (0.272107); 29 (0.727893)</td>
<td>28</td>
<td>0.529</td>
<td>12 (0.011818); 29 (0.173881); 33 (0.814300)</td>
</tr>
<tr>
<td>17</td>
<td>0.420</td>
<td>12 (0.154904); 19 (0.005365); 23 (0.020513); 33 (0.819218)</td>
<td>29</td>
<td>1.000</td>
<td>29 (1.000000)</td>
</tr>
</tbody>
</table>
CONCLUSION AND FUTURE RESEARCH DIRECTION

This study aims to measure the technical efficiency of large and medium manufacturing industries in Central Java Province, Indonesia. DEA with output-oriented and variable returns-to-scale approach is used to accomplish the objective of the study. Result shows that among 24 DMUs under-investigated, six of them are considered as the most efficient, located at the frontier (see Table 2).

This study calls for future research by comparing the finding with the study about measuring technical efficiency of small and micro manufacturing industries as this can give a more holistic portrait of the condition of manufacturing industries in Indonesia. Another future research direction is to perform the analysis in a panel data setting. Using panel data, more information of efficiency can be parsed, and in particular, shed light on changes in efficiency; whereas contrarily, in a cross-sectional setting (as in this study), it can only provide a static portrayal of efficiency.

REFERENCES


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