OmniaScience

Journal of Industrial Engineering and Management
JIEM, 2022 – 15(4): 521-537 – Online ISSN: 2013-0953 – Print ISSN: 2013-8423
https://doi.org/10.3926/jiem.4022

Evaluating the Efficiency and Productivity of Malaysian Logistics Companies Using Epsilon-Based Measure and Malmquist Index during the Covid-19 Pandemic

Nur Annisa Ezzaty Rusli[1], Noor Asiah Ramli[2], S. Sarifah Radiah Shariff[2], Zalina Zahid[2], Siti Aida Sheikh Hussin[2]

[1]*Mont Royale College, Kuala Lumpur (Malaysia)*
[2]*Universiti Teknologi MARA, Shah Alam (Malaysia)*

nurannisaezzaty.rusli@gmail.com, asiah2206@uitm.edu.my, shari990@uitm.edu.my, zalin405@uitm.edu.my, sitiaida842@uitm.edu.my

Received: April 2022
Accepted: July 2022

Abstract:

Purpose: The impact of the Covid-19 outbreak since March 2020 has put Malaysia's logistics sector in a contrasting reality to other sectors, as during the implementation of the movement control order (MCO), this sector was declared as providing essential service and allowed to operate in order to fulfil customers' needs. This study aims to assess the efficiency and productivity of the logistics industry in Malaysia before and during the pandemic so that the performance of this industry can be observed.

Design/methodology/approach: This study uses secondary data. Yearly records from the annual reports for the period of 2010-2020 were gathered pertaining to 15 Malaysian logistics companies treated as decision making units (DMUs) in this study. The efficiency and productivity of the Malaysian logistics industry during the Covid-19 pandemic have been assessed by using a hybrid DEA model consisting of a combination of epsilon-based measure (EBM) and Malmquist index.

Findings: Findings showed that Lingkaran Trans Kota Holdings Berhad was the most efficient and productive logistics company with an average efficiency score of 1 and 12.7% growth in the average productivity index during the study period. In contrast, MISC Berhad obtained the lowest average efficiency score of 0.285. Nevertheless, the average productivity index for MISC Berhad showed an increase by 25.7%. During the early outbreak of Covid-19, Complete Logistics Services Berhad achieved full efficiency and also attained the highest positive growth of 76.2%. Harbour-Link Group Berhad was the least efficient company, scoring an efficiency score of only 0.254 and a decline in productivity growth by 40.8%.

Research limitations/implications: The data used in this study may not be sufficient to represent the performance of the entire logistics industry as the pandemic is still not completely over. More useful insights can be obtained if the data can be extended until 2022 to assess the performance of logistics companies after the outbreak of Covid-19 in Malaysia. Many resources that have not been explored in this study and past research may provide an avenue for further research on the performance measurement of logistics companies, particularly in the Malaysian context.

Practical implications: This study's discovery may be used to facilitate the evaluation of resource utilisation and help inefficient logistics companies maximise their efficiency. Also, the findings may be used to help policymakers evaluate the existing policy in order to ensure that logistics companies have sufficient resources to offer reliable and efficient courier services.

Originality/value: Although numerous studies have been conducted on the efficiency measurement of logistics companies, so far, scarce research in Malaysia has deployed a quantitative approach to measure the performance of Malaysia's logistics industry, especially during the Covid-19 pandemic. Therefore, this study fills this gap by assessing the efficiency and productivity of the logistics industry in Malaysia before and during the pandemic of Covid-19.

Keywords: efficiency, productivity, epsilon-based measure (EBM), Malmquist index, logistics

To cite this article:

Rusli, N.A.E., Ramli, N.A., Shariff, S.S.R., Zahid, Z., & Hussin, S.A.S. (2022). Evaluating the efficiency and productivity of Malaysian logistics companies using epsilon-based measure and malmquist index during the Covid-19 pandemic. *Journal of Industrial Engineering and Management*, 15(4), 521-537. https://doi.org/10.3926/jiem.4022

1. Introduction

Logistics can be defined as a general strategy for handling the procurement, movement, and storage of raw materials, semi-finished goods, and finished goods, including the associated information flows on how to transport finished goods to end customers by an organisation and its marketing channel. Logistics activities can be categorised into inbound and outbound logistics (Lummus, Krumwiede & Vokurka, 2001). Both terms refer to the transportation and movement of goods through the supply chain. Inbound logistics are concerned with businesses receiving inventory such as raw materials and goods directly from manufacturers and suppliers, whereas outbound logistics entail the delivery and shipping out of finished goods and products to final customers, where the order fulfilment processes involve picking, packing, shipping, and delivering packages.

According to the study conducted by Mohamad-Makmor, Saludin and Saad (2019), the Malaysian logistic industry exhibited a decreasing pattern in performance based on the Logistics Performance Index (LPI) issued by International Trade and Transport Department of World Bank. Malaysia was ranked 41st out of 160 countries in 2018, 32nd in 2016, and 25th in 2014. In tandem with the rising competitiveness of the global economy, performance measurement of the logistics industry is crucial to all businesses, especially small and medium enterprises (SME) that conduct their businesses online. The performance measurement can inspire the entire industry to improve, which will impact the growth of the overall economy (Bao, Ramlan, Mohamad & Yassin, 2018). Thus, the analysis and design of the performance evaluation is vital towards enhancing logistics management.

The spread of Covid-19 since March 2020 has a different impact on the logistics sector relative to other sectors. The Covid-19 outbreak has disrupted almost all economic sectors (Zhu, Chou & Tsai, 2020). Agriculture; oil, gas, and energy; tourism; retail; private healthcare; and many other industries are severely affected by the pandemic (Atayah, Dhiaf, Najaf & Frederico, 2021; Rajaratnam & Sunmola, 2021; Sopha, Arvianto & Tjahjono, 2022). The government of Malaysia imposed several restrictive measures to curb the spread of the pandemic such as travel restrictions, border closures, large-scale quarantines, bans on large-scale gatherings and dining in restaurants, and partial lockdowns (Budd & Ison, 2020). Therefore, several of society activities and business operations were forced to cease. The pandemic has affected the whole society where people are afraid to go out, especially in crowded areas such as shopping malls and groceries stores. The Covid-19 virus is transmitted through people's contact with each other and a lack of social distancing. Due to this circumstance, customers prefer online shopping as it involves less contact with people and reduces the Covid-19 transmission.

Malaysia is regarded as one of the attractive markets for digitalisation in Southeast Asia due to its developed infrastructure and advanced digital technologies. Hence, it is not surprising to find that online payment websites, online shopping sites, e-marketplaces, and logistics services have mushroomed in the country. As a result, online sales in Malaysia have skyrocketed (Kim, 2020). During the pandemic, people need to stay at home especially if they are infected. Thus, the demand for essential products through online shopping platforms increases rapidly, and the pressure to deliver purchases now falls on logistics companies. Therefore, the impact of the Covid-19 outbreak has put Malaysia's logistics sector in a contrasting reality to other sectors, as during the implementation of the movement control order (MCO), this sector was declared as providing essential service and allowed to operate in order to fulfil customers' needs.

This scenario has pushed the logistics industry to re-evaluate and re-strategise its operations towards digitalisation in order to increase customer satisfaction, especially during the pandemic. Although numerous studies have been conducted on the efficiency measurement of logistics companies, so far, scarce research in Malaysia has deployed a quantitative approach to measure the performance of Malaysia's logistics industry, especially during the Covid-19 pandemic. Therefore, this study fills this gap by assessing the efficiency and productivity of the logistics industry in Malaysia before and during the pandemic by using a hybrid data envelopment analysis (DEA) model consisting of a combination of epsilon-based measure (EBM) and Malmquist productivity index (MPI). An appropriate technique should be employed to measure the efficiency of Malaysia's logistics companies, particularly during the pandemic, so that the performance of this industry can be observed.

2. Literature Review

Efficiency is a relative measure which uses various types of inputs and outputs from a sample and converts them into efficiency and inefficiency frontiers. Studies have discovered the proportion of two linear combinations that will derive efficiency score (Bao et al., 2018; Nguyen & Tran, 2019). Haynes (2007) described efficiency as the proportion of the expected resources to those used and productivity as the ratio of output over input measured by some values of cost. Meanwhile, technical efficiency is defined as the physical performance of an operation, where it specifically quantifies the relative capacity of a company to obtain a maximum number of outputs by using a given number of inputs. In other words, it shows the correlation between a specific number of inputs and outputs. Technical efficiency is more suitable to be used by companies that operate on the production frontier (Alemu, Tegegne & Beshir, 2018; Taib, Ashraf & Razimi, 2018).

When more researchers started to explore the two conventional DEA methods, namely CCR (Charnes, Cooper & Rhodes, 1978) and BCC (Banker, Charnes & Cooper, 1984), these methods were found to ignore non-radial slacks when measuring efficiency scores. Therefore, Färe and Lovell (1978) introduced the first non-radial model known as the Russell measure (Pastor, Ruiz & Sirvent, 1999). Tone (2011) started analysing the Russell measure and introduced a new non-radial model called slack-based measure (SBM). SBM can handle slacks in efficiency scores but ignores the input and output variances. The model deals directly with the excess of input and the shortage of output slacks, and later integrates them into an efficiency measure. To eliminate the shortcoming of ignoring the input and output variances, at the same time, Tone and Tsutsui (2010) introduced a hybrid model known as the composite model and is now referred to as epsilon-based measure (EBM). This model is a comprehensive evaluation method that considers the assumption of a proportionate contraction in inputs and outputs and the existence of slack for each input and output, defined in both radial and non-radial characteristics of input and output measures. Thus, this study selected the EBM model in the DEA framework due to its popularity for measuring efficiency.

Efficiency and productivity are important aspects of economic performance. Productivity measurements are widely used to assess the changes in economic efficiency over a time period besides variations in efficiency at a particular time (Tannady & Maimury, 2018). Efficiency measurements can indicate productivity performance, and in turn, productivity performance can determine a country's economic growth. For all countries, productivity growth plays a significant role in economic development. One of the approaches for measuring productivity growth is Malmquist productivity index (MPI). This approach uses the distance function technique in measuring the productivity index. It was introduced by Malmquist (1953) and developed by Caves, Christensen and Diewert (1982). Färe and Lovell (1978) extended Malmquist index to the so-called DEA-Malmquist index to be used for evaluating and assessing productivity that changes over time. After the study done by Färe and Lovell (1978), various studies began to analyse the foundation, framework, and decomposition of DEA-Malmquist index. Some recent studies have applied the DEA-Malmquist index to measure productivity levels using different types of samples (e.g., Nguyen & Tran, 2019; Ling, Kokkiang, Gharleghi & Fah, 2018; Yu, 2021; Chandraprakaikul & Suebpongsakorn, 2012).

In the last decade, many studies have analysed the efficiency and productivity performance of logistics companies. Wu, Wu, Liang and Li (2012) applied the BCC-DEA model, CCR-DEA model, non-increasing returns to scale (NIRS) model, and super-efficiency DEA (SUP-DEA) to compute the relative measurement of efficiency of 36 major logistics companies listed in Shanghai and Shenzhen, China stock exchanges in 2006. They found a comparatively low overall efficiency score for the logistics companies in China. Besides, DEA was suggested to be a practical and sensible technique in evaluating logistics companies' performance. Similar models were deployed in a study conducted by Park and Lee (2015), which used both CCR-DEA and BCC-DEA to examine the level of efficiency of 14 certified logistics companies in Korea. The CCR model was found to be more accurate on technical efficiency, while the BCC model was used for pure technical efficiency. The analysis showed that Pantos Logistics and HYUNDAI Glovis scored the highest efficiency level, and Hanjin Transportation was the most stable company in logistics operations.

A study conducted by Mokhtar, Hussein, Samo, Kader and Abd (2016) adopted the combination of SBM and super slack-based measure (SSBM) to measure the operational risk and efficiency of container terminals. A sample in Peninsular Malaysia consisting of six container terminals was retrieved for 8 years from 2003 to 2010. The results showed that the resources allocation efficiency needed to be enhanced to obtain superior results. For both models above, there was no significant adjusted risk related to equipment, planning, cargo volume, and size. Wang, Day and Nguyen (2018) benchmarked the efficiency levels of 10 large third-party logistics (3PL) providers and predicted their efficiency scores to help consumers choose the best 3PL providers. Two models were proposed, namely grey forecast model and EBM model in DEA. Results showed that among the 115 cases, 36 were efficient and the rest were not. Seven 3PL providers exhibited upward and downward patterns in their efficiency scores. Another study that measured efficiency was conducted by Bajec and Tuljak-Suban (2019). The study proposed an integrated analytic hierarchy process (AHP) and the SBM DEA model, based on the assumption of variable return to scale (VRS). The study used 18 logistics service providers (LPs) in Slovenia as a sample. The SBM DEA model results showed that most of the LPs were inefficient.

Since the outbreak of Covid-19 at the end of 2019, many studies have been conducted to observe the impact of the pandemic on logistics companies. A study by Wang, Nguyen, Fu, Hsu and Dang (2021) evaluated the efficiency of 14 seaport terminal operators in Vietnam using DEA Malmquist and EBM model. The EBM model showed that nearly all companies were fully efficient in 2020 despite the global economic downturn triggered by the pandemic. As for productivity growth, it was discovered that there was only a small number of fluctuating shapes of seaport terminal operators throughout the study period. Another research that examined the impact of the Covid-19 pandemic on the logistics industry was conducted by Nguyen (2021). The study used MPI to assess productivity growth from 2017 to 2020 and summarised that logistics businesses were severely impacted by the Covid-19 pandemic as shown by the dramatic fluctuations of the productivity growth. In a recent article, Fun, Siew and Hoe (2022) examined the financial performance of listed logistics companies in Malaysia using the standard DEA model. The study found that less than 50% of logistics companies were efficient. The findings were then used to benchmark all the inefficient logistics companies for financial and operational improvements.

Very few studies have measured the efficiency and productivity of the logistics industry in Malaysia. Therefore, this study is hoped to contribute to the existing literature on the impact of the Covid-19 pandemic on Malaysia's economic growth.

3. Data and Methodology

This study uses secondary data. Yearly records for the period of 2010-2020 were gathered pertaining to 15 Malaysian logistics companies treated as decision making units (DMUs) in this study. The list of DMUs is presented in Table 1.

Category	Logistics Companies	DMUs
Transportation and Logistics Services	Ancom Logistics Berhad	DMU1
	Malaysia Airports Holdings Berhad	DMU2
	GD Express Carrier Berhad	DMU3
	Harbour-Link Group Berhad	DMU4
	Hubline Berhad	DMU5
	Malaysian Bulk Carriers Berhad	DMU6
	MISC Berhad	DMU7
	MMC Corporation Berhad	DMU8
	Tiong Nam Logistics Holdings Berhad	DMU9
	CJ Century Logistics Holdings Berhad	DMU10
	Complete Logistics Services Berhad	DMU11
	Freight Management Holdings Berhad	DMU12
	Lingkaran Trans Kota Holdings Berhad	DMU13
	See Hup Consolidated Berhad	DMU14
	Suria Capital Holdings Berhad	DMU15

Table 1. DMUs for the study

The study decided to retrieve the dataset from Bursa Malaysia due to ease of access to the companies' annual financial reports on the bourse's website. Data on companies can be easily extracted from their annual financial reports disclosed as company announcements on Bursa Malaysia's website. The variables examined in the study consist of three inputs and two outputs (see Table 2).

Category	Variables	Description
Input (x)	Current Assets (CA)	Cash and any other assets/resources that are expected to be consumed, used or converted to cash within one year.
	Net Fixed Assets (NFA)	Net value of fixed assets in company after discarding the depreciation of expenses, impairment expenses and liabilities that the entity used to procure fixed assets.
	Current Liabilities (CL)	Firms' short-term financial obligation that must be repaid within one year.
Output (y)	Operating Income (OI)	Earnings Before Interest and Taxes (EBIT). It is also known as a revenue left in company after removing operational direct and indirect expenses from sales revenue.
	Revenue (R)	Profit or income earned from company by selling products and/or services measured over a set period.

Table 2. Input and output variables of the study

The model used to attain the efficiency score is EBM. Before measuring the efficiency score using EBM, the diversity index and affinity index need to be verified to fulfil the condition of EBM. This step can also help to determine the correlation between all the selected variables. The purpose of using EBM is to determine the efficiency and inefficiency scores of DMUs to measure their technical efficiencies based on three inputs and two outputs. Next, MPI is employed to ascertain the total productivity index of the 15 DMUs. Finally, the results of the analysis and discussion pertaining to Malaysia's logistics industry before and during the Covid-19 pandemic are presented.

3.1. Epsilon-Based Measure (EBM)

This study uses n number of DMUs, with each DMU denoted by DMU_i, where (i = 1, …, n). Each DMU has m number of inputs (j = 1, …, m) and r number of outputs (s = 1, …, r). The input of DMU_i is denoted by

$X = \{x_{ij}\} \in R^{m \times n}$, and the output of DMU_i is denoted by $Y = \{y_{ij}\} \in R^{n \times r}$. $X > 0$ and $Y > 0$ hold. The objective function of the input-oriented CCR model with CRS EBM input oriented constant return to scale (EBM-I-C) is shown in Equation 1.

$$\gamma^* = min\theta - \varepsilon_x \sum_{i=1}^{m} \frac{\omega_i^- s_i^-}{x_{io}}$$

$$\text{Subject to} = \begin{cases} \theta x_0 - X\lambda - s^- = 0 \\ Y\lambda \geq 0 \\ \lambda \geq 0 \\ s^- \geq 0 \end{cases} \tag{1}$$

Where,

γ^*: Individual sample indexed with i

θ: Radial efficiency value computed by the CCR model

λ: The vector's weight

ω_i^-: The weight of input j. Note that $\sum_{j=1}^{m} \omega_i^- = 1$ and $\omega_i^- \geq 0$

εx: A parameter that combines radical efficiency, θ, and non-radical slack terms

Altogether, there are five steps involved in calculating the efficiency scores of all DMUs using the EBM-I-C. The steps are listed below (see Tone & Tsutsui [2010] for detailed explanation). The results for each step will be discussed in the next section.

Step 1 Find the projected CRS-efficient DMUs

Step 2 Form the diversity index and affinity index

Step 3 Find the eigenvector and largest eigenvalue of the affinity index

Step 4 Compute εx and ω^- for the EBM from the largest eigenvalue and eigenvector, respectively

Step 5 Find the efficiency score of EBM using εx and ω^-

3.2. Projected DMUs

Variable slacks should be calculated before defining the projected input and output (Tone & Tsutsui, 2010). By projecting the input and output variables, the result estimation in the study will be increased. After computing the slack variables using equation 2, the projected input and output can be measured using the formulas in equations 3 and 4, respectively.

$$max \sum_{i=1}^{m} \frac{S_i^-}{x_{i0}} + \sum_{i=1}^{s} \frac{S_i^+}{y_{i0}} \tag{2}$$

$$\text{Subject to} = \begin{cases} x_{i0} = \sum_{j=1}^{n} x_{ij}\lambda_j + S_i^- \\ y_{i0} = \sum_{j=1}^{n} y_{ij}\lambda_j - S_i^+ \\ \sum_{j=1}^{n} \lambda_j = 1 \\ \lambda_j \geq 0 \\ S_i^+ \geq 0 \\ S_i^- \geq 0 \end{cases} \tag{3}$$

$$\begin{gathered} \bar{x}_{io} = x_{io} - S_i^{-*} \\ \bar{y}_{io} = y_{io} + S_i^{+*} \end{gathered} \tag{4}$$

3.3. Diversity and Affinity Index

Pearson's correlation coefficient interprets original and unedited data (Wang et al., 2018). Thus, it is not suitable to be used in finding the epsilon value. Therefore, the diversity index and affinity index are used in this study. $S(x, y)$ is the affinity index between vectors p and q that followed by several properties. The affinity index is calculated using $S = \{S_{ij}\} \in R^{m \times m}$ with the elements in equation 5. All the elements in index S need to fulfil the following properties.

$$S_{ij} = S(\bar{X}_i, \bar{X}_j)(i, j = 1, \dots, m) \tag{5}$$

(Property1): $S(x, y)$ equals to 1, which is identical

(Property2): $S(x, y)$ equals to $S(y, x)$, which is symmetrical

(Property3): $S(tx, y) = S(x, y)$ where $t > 0$

(Property4): $0 \leq S(x, y) \leq 1$

The above equation is simplified by setting the affinity index according to equation 6 below:

$$S(x, y) = 1 - 2H(x, y) \tag{6}$$

Before establishing the affinity index, the diversity index of the observed inputs should be computed by using the formula below. Let Dj be the deviation in the diversity index of vectors p and q, $\overline{D}$ be the average of the deviation in the diversity index, and $H(p, q)$ be the coefficient of the diversity index, as shown in Equations 7, 8, and 9, respectively. The diversity index must be in the range of 0 to 0.5 so that the properties of the affinity index can be satisfied $[0 \leq H(p, q) = H(q, p) \leq 1/2]$.

$$D_j = ln\left(\frac{x_j}{y_j}\right), j = 1, \dots, n \tag{7}$$

$$\bar{D} = \frac{1}{n}\sum_{j=1}^{n} D_j \tag{8}$$

$$H(x, y) = \begin{cases} \dfrac{\sum_{j=1}^{n}\left|D_j - \bar{D}\right|}{n(D_{max} - D_{min})}(if D_{max} > D_{min}) \\ 0(if D_{max} = D_{min}) \end{cases} \tag{9}$$

3.4. Computing εx and ω^- for the EBM

According to Tone and Tsutsui (2010), S is a non-negative and symmetric matrix, where the diagonal matrix generated from S is equal to unity. S will have m pairs of eigenvalue and $m \times m$ eigenvector ($w_x \geq 0$), and the largest eigenvalue, ρx, will be used to find the epsilon value (refer to Equation 10). Only non-negative w_x is proportionate with the weight, ω^-, of the input factors, whereby ω^- of EBM can be obtained using the formula in Equation 11. Since S is non-negative definite, the study defines $m \geq \rho x \geq 1$.

$$\varepsilon_x = \begin{cases} \dfrac{m - \rho_x}{m - 1} if\ (m > 1) \\ 0 if (m = 1) \end{cases} \tag{10}$$

$$w^- = \frac{w_x}{\sum_{i=1}^{m} w_x} \tag{11}$$

3.5. Malmquist Productivity Index (MPI)

The Malmquist productivity index (MPI) is established using the distance function. With a given number of inputs, a distance function is used to obtain the uttermost proportional expansion of the output (Mahadevan, 2002). MPI is used to evaluate the productivity change in DMUs between two time periods (Al-Eraqi, Khader & Mustafa, 2009). The mathematical equation of MPI was first introduced by Färe and Grosskopf (1992), where the output-oriented Malmquist productivity change index between time t and t+1 is as per Equation 12. Equation 12 shows an equivalent way of expressing the productivity index. According to Wang et al. (2021), an MPI value that is greater than 1 indicates that the specific DMU has positive productivity growth from time t to t+1.

$$M_1^{t+1}(y^{t+1},x^{t+1},y^t,x^t) = \left(\frac{D_1^t(y^{t+1},x^{t+1})}{D_1^t(y^t,x^t)} \times \frac{D_1^{t+1}(y^{t+1},x^{t+1})}{D_1^{t+1}(y^t,x^t)}\right)^{\frac{1}{2}} \tag{12}$$

where;

$M_1^{t+1}(y^{t+1}, x^{t+1}, y^t, x^t)$	Production's productivity from period (t+1) for the point $x_k^{t+1} + y_k^{t+1}$ relative to the period (t) for the point $x_k^t + y_k^t$
x	Input variable
y	Output variable
$D^{t+1}(y^t, x^t)$	Distance from period t observation to period $t + 1$

4. Finding

In this section, EBM-I-C is used to rank the technical efficiency of 15 DMUs for the 11-year period from 2010 to 2020. The statistical description of the historical dataset is shown in Table 3. Meanwhile, Table 4 until Table 8 present the outputs obtained from Step 1 to Step 5 to obtain the efficiency scores from EBM and the productivity index from MPI.

Table 3 shows the summary statistics of the variables. The year 2020 shows the highest values for all inputs and outputs. Meanwhile, the lowest values of current assets (CA) and current liabilities (CL) are derived for 2010, net fixed assets (NFA) for 2013, operating income (OI) for 2016, and revenue (R) for 2020. Besides, two of the variables (NFA and CL) show the highest average in 2018 and another two variables (CL and R) show the highest standard deviation in 2012.

	Years	CA	NFA	CL	OI	R
Max	2010	398525049	649939157	222579338	32453069	634442927
Min		75376	1654	41709	959	237772
Average		45049019.33	70550820.27	27104875.73	6157516	83964637.53
SD		103402866.3	171940329.5	58709800.68	10513439.73	173337673.5
Max	2011	358060245	622784051	270242990	20206939	569927941
Min		93296	1213	52554	12095	253325
Average		42347259.13	69684220.87	31175201.53	4918038.867	84704573.2
SD		93790465.25	165890361.4	71058155.25	7234685.005	164786658.3
Max	2012	278731546	619186144	275291681	35230190	499063491
Min		107085	715	51706	326	248377
Average		40933470.53	67637261.07	35775652.4	5039795.933	89868214.87
SD		82916640.64	160536543.2	76932397.47	9775227.225	167593562.9

	Years	CA	NFA	CL	OI	R
Max	2013	199353464	531371613	179187155	24063593	422707999
Min		130845	368	55455	610	246744
Average		34661874.67	61706055.4	26801062	5901293	77823969.93
SD		63666076.26	138816532.5	54908059.84	9082153.454	140570288.6
Max	2014	224633588	508003109	178423070	51023288	506963059
Min		136215	943	57391	20849	255724
Average		38467610.47	62178590.13	28667639.27	7944964.667	66089548.73
SD		68799429.21	133137369	56230861.14	14545401.18	133035689.1
Max	2015	310795286	222487025	214968346	31306481	506963059
Min		156758	1265	63983	1031	241501
Average		41441814.73	42184337.27	33475278.53	8277471.067	69736674.6
SD		83054159.82	70130822.63	68302983.05	12561443.6	135642638.8
Max	2016	366552720	195523104	152607109	101960567	590764421
Min		156844	1291	71570	255	225505
Average		52114385.6	37188174.4	22309932	12437902	75128429.67
SD		117918588.4	57721171.51	44672826.58	27402312.48	156482970.4
Max	2017	371890746	287167475	154997336	46751424	525745860
Min		168166	1555	68179	1787	272582
Average		52559189	46322353.33	22288206.6	8167838.667	73237162.53
SD		120202700	79102887.68	44068826.15	16142480.42	143729423.9
Max	2018	376343548	142876111	135999240	59506464	615799853
Min		194323	1289	80068	1256	238974
Average		58264342.73	32125619.8	20534509.07	9410146.2	83443635.4
SD		120866511.3	47590479.88	37732570.95	18368343.47	168040097.8
Max	2019	374816477	169539229	133221951	41907654	593951033
Min		201198	1142	84949	1012	250456
Average		59700613.73	37243272.53	22963922	7561806.533	85047934.93
SD		120199683.5	55352791.85	39964801.21	13580242.24	165398976.1
Max	2020	386465526	250881209	128510821	35037932	364009954
Min		118657	754	75885	723	175986
Average		63620116.2	45242854.6	25521996.8	5801375.467	57075322.07
SD		124679971.9	79842694.73	45161341.42	10818388.25	100224572.9

Table 3. Descriptive statistics of inputs and outputs from 2010 to 2020

Table 4 presents the diversity index (H) and affinity index (S) in the EBM model for the 11-year period. Since the study is input-oriented, only three chosen inputs are considered for the diversity index and affinity index. As the table shows, the diversity index values range from 0 to 0.2620 (year 2013), while the affinity index values range from 0.4760 (year 2013) to 1. These values satisfy the conditions of $0 \leq H(x, y) \leq 0.5$ and $0 \leq S(x, y) \leq 1$. Hence, the next step, which is computing the weight to input/output, can be carried out.

		Diversity Index (H)			Affinity Index (S)		
	Years	CA	NFA	CL	CA	NFA	CL
CA	2010	0.0000	0.1916	0.2294	1.0000	0.6168	0.5412
NFA		0.1916	0.0000	0.1901	0.6168	1.0000	0.6199
CL		0.2294	0.1901	0.0000	0.5412	0.6199	1.0000
CA	2011	0.0000	0.1933	0.1651	1.0000	0.6135	0.6698
NFA		0.1933	0.0000	0.1933	0.6135	1.0000	0.6135
CL		0.1651	0.1933	0.0000	0.6698	0.6135	1.0000
CA	2012	0.0000	0.1822	0.2124	1.0000	0.6356	0.5751
NFA		0.1822	0.0000	0.1743	0.6356	1.0000	0.6513
CL		0.2124	0.1743	0.0000	0.5751	0.6513	1.0000
CA	2013	0.0000	0.1578	0.2620	1.0000	0.6845	0.4760
NFA		0.1578	0.0000	0.1480	0.6845	1.0000	0.7040
CL		0.2620	0.1480	0.0000	0.4760	0.7040	1.0000
CA	2014	0.0000	0.1404	0.2333	1.0000	0.7193	0.5335
NFA		0.1404	0.0000	0.1577	0.7193	1.0000	0.6847
CL		0.2333	0.1577	0.0000	0.5335	0.6847	1.0000
CA	2015	0.0000	0.1401	0.2487	1.0000	0.7198	0.5026
NFA		0.1401	0.0000	0.1426	0.7198	1.0000	0.7148
CL		0.2487	0.1426	0.0000	0.5026	0.7148	1.0000
CA	2016	0.0000	0.1471	0.1509	1.0000	0.7058	0.6981
NFA		0.1471	0.0000	0.1677	0.7058	1.0000	0.6645
CL		0.1509	0.1677	0.0000	0.6981	0.6645	1.0000
CA	2017	0.0000	0.1269	0.1308	1.0000	0.7462	0.7383
NFA		0.1269	0.0000	0.1493	0.7462	1.0000	0.7015
CL		0.1308	0.1493	0.0000	0.7383	0.7015	1.0000
CA	2018	0.0000	0.1736	0.1749	1.0000	0.6527	0.6502
NFA		0.1736	0.0000	0.1707	0.6527	1.0000	0.6586
CL		0.1749	0.1707	0.0000	0.6502	0.6586	1.0000
CA	2019	0.0000	0.1713	0.2052	1.0000	0.6573	0.5896
NFA		0.1713	0.0000	0.1722	0.6573	1.0000	0.6555
CL		0.2052	0.1722	0.0000	0.5896	0.6555	1.0000
CA	2020	0.0000	0.1318	0.1779	1.0000	0.7364	0.6442
NFA		0.1318	0.0000	0.1297	0.7364	1.0000	0.7405
CL		0.1779	0.1297	0.0000	0.6442	0.7405	1.0000

Table 4. Diversity index and affinity index from 2010 to 2020

Table 5 shows that all weights are positive, with values ranging from 0.3193 to 0.3574. The sum of three inputs weights is equal to 1 for each year. The same table also displays the key parameter that combines non-radial and radial components, which is epsilon of the EBM model. The epsilon values are positive, ranging from 0.2741 (year 2017) to 0.4430 (year 2010).

Years	Weight (CA)	Weight (NFA)	Weight (CL)	Epsilon
2010	0.3283	0.3427	0.3290	0.4430
2011	0.3367	0.3266	0.3367	0.3272
2012	0.3279	0.3413	0.3308	0.3903
2013	0.3193	0.3574	0.3233	0.3708
2014	0.3275	0.3516	0.3209	0.3498
2015	0.3224	0.3562	0.3214	0.3683
2016	0.3373	0.3320	0.3307	0.2811
2017	0.3374	0.3319	0.3307	0.2741
2018	0.3325	0.3339	0.3335	0.3608
2019	0.3297	0.3410	0.3293	0.3814
2020	0.3282	0.3429	0.3289	0.2844

Table 5. Weight of input/output and epsilon from 2010 to 2020

Based on the epsilon values of the EBM model, weight to input/output and theta of the CCR model, the relative efficiency and inefficiency scores of the 15 DMUs are calculated, as displayed in Table 6. A value equals to 1 can be interpreted as fully efficient, whereas a value that is less than 1 indicates inefficiency. The empirical analysis results denote that DMU12 and DMU13 achieved full efficiency, always scoring 1 during the study period. However, DMU8, DMU9, and DMU10 never achieved full efficiency during the study period as all the scores are below 1. Thus, actions should be taken to improve the technical efficiency, i.e., minimising the current assets inputs such as labour and equipment supplies besides making changes to technological investments such as focusing on technology development so that the companies can maximise outputs such as operating income and revenue.

Table 6 also shows that the average efficiency scores are the highest in 2010 and the lowest in 2016. This phenomenon might be attributed to the financial crisis in April 2015. After the implementation of goods and services tax (GST) by the Malaysian government, Malaysia faced economic challenges such as a weakened ringgit, an oil and gas crisis, a loss in market confidence due to financial scandals, slower market activity leading to retrenchments and job cuts, and persistently increasing cost of living even with stagnant wages. Besides, some of the prices of the goods in Customer Price Index (CPI) also increased after the GST implementation (Loong, 2015). These factors might have affected the logistics industry.

Based on the total factor productivity index displayed in Table 6, logistics companies increased their average annual technical efficiency by 16.5% during the study period. Among the companies that made progress in the total factor productivity change (tfpch), DMU5 (48.1%) made the highest progress. In other words, Hubline Berhad recorded positive growth of 48.1% during the 10-year period. The remaining 14 Malaysian logistics companies also experienced positive productivity growth, namely Ancom Logistics Berhad (28.1%), Complete Logistics Services Berhad (27.1%), MISC Berhad (25.7%), Malaysian Bulk Carriers Berhad (25.1%), Malaysia Airports Holdings Berhad (24.9%), MMC Corporation Berhad (24.6%), Harbour-Link Group Berhad (20.3%), Lingkaran Trans Kota Holdings Berhad (12.7%), CJ Century Logistics Berhad (6.1%), Suria Capital Holdings Berhad (5.8%), Freight Management Holdings Berhad (4.5%), See Hup Consolidated Berhad (2.3%), GD Express Carrier Berhad (1.9%), and Tiong Nam Logistics Holdings Berhad (1.5%). Based on the average of productivity change for the 11-year period, none of the logistics companies experienced negative growth from 2011 to 2020. Thus, it can be concluded that the productivity of Malaysian logistics companies showed positive growth during the study period albeit some companies only recorded marginal growth.

Figure 1 displays the average efficiency score and productivity index for each DMU for the 11-year period. When a logistic company is said to be efficient, it must also be productive in managing its business. The findings show that DMU13 (Lingkaran Trans Kota) was the most efficient and productive logistics company during the study period with an average efficiency score of 1 and average productivity index of 1.127. In other words, DMU13 experienced positive growth of 12.7% during the study period. Meanwhile, DMU7 (MISC Berhad) was the least efficient with an average efficiency score of 0.285, as all the efficiency scores during the 11-year period are below 1. Nevertheless, the average productivity index for DMU7 is 1.257, indicating that DMU7 experienced progressive growth of 25.7% during the study period.

Years/ DMUs	Efficiency Score of EBM												Tfpch
	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Mean	2010-2020
DMU1	1.00	1.00	1.00	0.92	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.281
DMU2	0.40	0.50	1.00	1.00	0.31	0.50	0.33	0.33	0.41	0.40	0.31	0.51	1.249
DMU3	1.00	1.00	1.00	1.00	0.87	0.96	1.00	1.00	1.00	1.00	0.83	0.97	1.019
DMU4	0.67	0.73	0.76	0.62	0.79	0.64	0.92	0.72	1.00	1.00	0.25	0.74	1.203
DMU5	0.43	0.47	0.48	0.56	0.19	0.52	0.30	0.43	1.00	0.63	0.75	0.53	1.481
DMU6	1.00	1.00	0.42	0.41	0.39	0.27	0.22	0.34	0.18	0.40	0.50	0.41	1.251
DMU7	1.00	0.27	0.33	0.28	0.33	0.35	0.19	0.25	0.32	0.25	0.27	0.29	1.257
DMU8	0.29	0.37	0.37	0.28	0.32	0.75	0.24	0.25	0.38	0.40	0.48	0.38	1.246
DMU9	0.49	0.57	0.35	0.22	0.43	0.35	0.23	0.26	0.51	0.36	0.44	0.37	1.015
DMU10	0.86	0.72	0.72	0.51	0.61	0.71	0.66	0.71	0.72	0.80	0.73	0.69	1.061
DMU11	0.65	1.00	0.87	0.88	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	1.271
DMU12	1.00	1.00	1.00	1.00	1.00	1.00	0.97	1.00	1.00	1.00	1.00	1.00	1.045
DMU13	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.127
DMU14	1.00	1.00	1.00	0.74	0.79	1.00	0.80	0.86	0.69	0.76	0.95	0.86	1.023
DMU15	0.60	0.54	0.69	0.58	0.46	0.90	0.52	0.83	1.00	0.61	0.59	0.67	1.058
Mean	0.76	0.74	0.73	0.67	0.63	0.73	0.62	0.66	0.75	0.71	0.67	0.70	1.165

Table 6. Efficiency score and productivity index

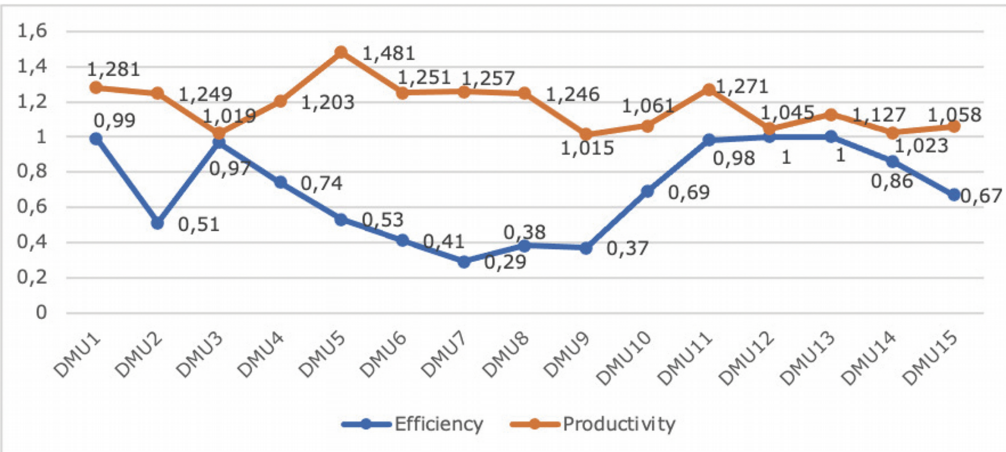

Figure 1. Efficiency score and productivity index of all DMUs 2010-2020

4.1. Performance of DMUs During the Covid-19 Pandemic

This study also evaluates the performance of Malaysian logistics companies during the early outbreak of Covid-19 using data 2020 for efficiency measurement. As for total factor productivity index, it is computed based on data from 2019 to 2020. Table 7 shows the total factor productivity index results from MPI and the efficiency scores generated from EBM for the 15 DMUs in 2020. DMU11 (Complete Logistics Services Berhad) achieved full efficiency, as indicated by its efficiency score of 1, and the highest positive growth of as much as 76.2% between 2019 and 2020. This score can be interpreted as DMU11 performed better during the early phase of the pandemic even though other logistics companies struggled to survive during the same period. DMU1 (Ancom Logistic Berhad) achieved the second highest productivity improvement with full efficiency. The company also experienced positive growth of around 47.5% in its operation from 2019 to 2020. Similarly, DMU12 (Freight Management Holdings Berhad) experienced strong positive efficiency and positive growth of 15.4% in its production during the pandemic. Likewise, DMU13 (Lingkaran Trans Kota Holdings Berhad) was fully efficient and had productivity growth of 30.7% during the early phase of the Covid-19 era.

DMUs	Tfpch	Efficiency Score	DMUs	Tfpch	Efficiency Score
DMU1	1.475	1.000	DMU9	1.122	0.443
DMU2	1.369	0.310	DMU10	0.673	0.732
DMU3	0.839	0.829	DMU11	1.762	1.000
DMU4	0.408	0.254	DMU12	1.154	1.000
DMU5	1.119	0.747	DMU13	1.307	1.000
DMU6	1.111	0.495	DMU14	1.489	0.951
DMU7	1.422	0.269	DMU15	1.194	0.594
DMU8	1.123	0.478	Average	1.153	0.673

Table 7. Total Factor productivity index and efficiency score for 15 DMUs in 2020

Three Malaysian logistics companies experienced a different scenario, in which the companies were inefficient and unproductive due to the impact of Covid-19. Meanwhile, eight Malaysian logistics company were inefficient but productive during the early phase of the Covid-19 era. The least efficient company was DMU4 (Harbour-Link Group Berhad) with an efficiency score of only 0.254 and productivity growth that declined by 40.8%. This phenomenon was due to the lowest revenue and operating income reported during the pandemic for the given inputs of CA, CL, and NFA.

5. Discussion

The results presented above show that some of the logistics companies perform better. For instance, Complete Logistics Services Berhad achieved full efficiency, as indicated by its efficiency score of 1 while See Hup Consolidated Berhad achieved almost fully efficient (0.951). This finding has been supported by a study conducted by Fun et al. (2022) in which they found that 41.18% of logistic firms are efficient including Complete Logistics Services Berhad. Besides that, Yingqi, Chang, Khoo, Yap and Muhamad (2018) also reported that it is one of the companies that achieved high efficiency in handling their operations and generating operating profit. Furthermore, Nguyen (2021) concluded that during the Covid-19 pandemic, there are still logistics businesses that operate very effectively.

Another study which is also consistent with this finding of productivity was presented by Abu-Bakar, Jaafar, Faisol and Muhammad (2014). They stated that there is a positive growth in the Malaysian logistics industry up until 2014. They also anticipated that the Malaysian logistics industry is expected to reach a positive level of development since numerous initiatives have been made by the Malaysian Government.

As a whole, the average efficiency score for all the 15 Malaysian logistics companies is 0.673, indicating that they were not highly efficient. As for the total factor productivity change, the average for all DMUs is positive growth of only 15.3% during the early phase of the Covid-19 outbreak. These results are in line with the findings reported in OECD Logistics Report (OECD, 2021) that the pandemic has caused disruptions to logistics companies in terms of operational constraints (delivery delays, congestion, and higher freight rates) and decreased demand in certain sectors.

6. Conclusion

This study employed the EBM model, in which the selected technique combines radial and non-radial models in a unified framework. The model was selected due to the shortcomings of radial CCR and non-radial SBM models, where they presume variance of inputs and outputs be change associated with slacks in inputs and outputs respectively. In addition, this study also applied Malmquist index to measure the productivity performance of logistics companies. Current assets, net fixed assets, and current liabilities were chosen as the inputs, while operating income and revenue were selected as the outputs. Efficiency and productivity are important aspects of economic performance. Efficiency measurements can indicate productivity performance, and in turn, productivity performance can determine a country's economic growth. Therefore, this analysis is very significance to observe the performance of logistics industry particularly in the Malaysian context during the Covid-19 pandemic.

Overall, DMU13 (Lingkaran Trans Kota Holdings Berhad) was the most efficient and productive logistics company with an average efficiency score of 1. DMU13 was fully efficient and experienced positive growth of 12.7% during the 11-year period from 2010 to 2020. Meanwhile, DMU7 (MISC Berhad) was the least efficient with an efficiency score of 0.285 for 2010-2020 and positive growth of 25.7%. This was because DMU7 experienced positive growth throughout the 10-year period except in 2015-2016 (0.967) and 2016-2017 (0.785), indicate declining productivity growth by 3.31% and 21.5%, respectively. This study also analysed the performance of the companies during the Covid-19 pandemic. DMU11 (Complete Logistics Services Berhad) achieved strong efficiency with an efficiency score of 1 and slack of 0, as well as the highest positive productivity growth of as much as 76.2% during the one-year period (2019-2020). On the other hand, DMU4 (Harbour-Link Group Berhad) was the least efficient company with an efficiency score of only 0.254 and productivity growth that declined by 59.2% from 2019 to 2020. This was due to the lowest revenue and operating income made during the pandemic for the given inputs of current assets, current liabilities, and net fixed assets.

This study's finding has several practical implications. The Malaysian government has classified logistics as an important industry. In the national transport policy 2019-2030, one of the policy thrusts is optimise, build, and maintain the use of transport infrastructure, services, and networks to maximise efficiency (OECD, 2021). Thus, this study's discovery may be used to facilitate the evaluation of resource utilisation and help inefficient logistics companies maximise their efficiency. Also, the findings may be used to help policymakers evaluate the existing policy in order to ensure that logistics companies have sufficient resources to offer reliable and efficient courier services.

In terms of empirical contribution, this study is especially useful in the Malaysian context, as scarce research in Malaysia has deployed a hybrid DEA model consisting of a combination of epsilon-based measure (EBM) and Malmquist index to measure the performance of Malaysia's logistics industry, especially during the Covid-19 pandemic. In addition, it is recommended that more studies be conducted to further explore the performance and issues pertaining to the logistics industry. For instance, the data used in this study may not be sufficient to represent the performance of the entire logistics industry as the pandemic is still not completely over. More useful insights can be obtained if the data can be extended until 2022 to assess the performance of logistics companies after the outbreak of Covid-19 in Malaysia. Many resources that have not been explored in this study and past research may provide an avenue for further research on the performance measurement of logistics companies, particularly in the Malaysian context. It may also be beneficial to examine logistics companies from other countries which may lead to better performance measurements. By exploring more logistics companies, the outcomes pertaining to their performance may be more reliable and meaningful to the government and policymakers.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The authors received financial support for the research, authorship, and/or publication of this article by Universiti Teknologi MARA (UiTM) under the Institut Pengangkutan Malaysia (Mitrans-EK) with project code:

RS12021GRN79RN001. The authors would like to acknowledge this financial support towards making this study a success.

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