

Evaluating the Courier and Delivery Services Company's Efficiency Using an EBM Model

Nguyen Ngoc Hiep*, Hoang Minh Tuan, and June Raymond L. Mariano

Abstract: The market for courier and delivery services is changing favorably as a result of the most recent and continuous technical developments in logistics. Thanks to real-time monitoring technology, which provides transparency and peace of mind, customers can now effortlessly keep a watch on their deliveries at every stage. This study aims to assess the efficiency of nine significant delivery and courier services. The EBM model was applied to assess efficiency from 2021 to 2024. According to the empirical data, Meituan's LO-05, Aramex PJSC's LO-08, and C.H. Robinson Worldwide's LO-09 all achieve high efficiency and maintain a steady efficiency score over the course of the term. Showing the rising and decreasing trends in each period for LO-03 (JD Logistics), LO-04 (SF Express), and LO-07 (PostNL N.V). Customers will be assisted in choosing the best organizations by the rising and falling variance index of the 09 courier & delivery service providers.

Keywords: Courier services companies, data envelopment analysis, EBM model, epsilon-based measure.

1. INTRODUCTION

Courier services are specialist logistics firms that offer prompt and dependable freight, document, and package transit between specified locations. To guarantee prompt and safe delivery, they frequently track goods and provide same-day or next-day delivery alternatives [1]. The three major type of courier services are business-to-business (B2B), business-to-customer (B2C), and customer-to-customer (C2C). The courier services sector has experienced substantial growth recently. Having a compound annual growth rate (CAGR) of 650.4%, it is projected to grow from \$458.48 billion in 2024 to \$483.04 billion in 2025. This study intends to evaluate the effectiveness of nine significant delivery and courier services. The EBM model has been used in evaluation efficiency from 2021 to 2024. Over the next five years, growth is expected to be 7.7%, which is 0.1 less than the prior estimate. By 2045, the world's urban population is expected to have increased by 1.5 times, to reach 6 billion people. As a result, the courier services sector is expanding due to growing urbanization. The courier industry is dominated by major corporations such as UPS, DHL, JD Logistics, and ZTO Express Inc. Leading businesses in the courier services sector are concentrating on creating cutting-edge solutions, like the launch of mobile applications. The market for courier

services includes the money made by companies that provide services like tracking and tracing, packing and labelling, expedited delivery, and customized delivery alternatives.

The Epsilon-Based Measured (EBM) approach is used in this study to assess efficiency and inefficiency loss within a single framework. This study uses the EBM method to rank each organization and discover inefficient and efficient units. These results aid in the identification of successful development plans for enhancing operational performance, resilience, and sustainability in courier services organizations.

The following are included in this study to analyze its impact: An overview of the study, including the courier service providers, is provided in (1). (2) examines the EBM method literature. (3) identifies the data sources, calculates the input and output for the EBM techniques, and provides the analysis and results. (4) offers the discussion, findings, restrictions, and upcoming research.

2. LITERATURE REVIEW AND METHODOLOGY

2.1. Literature review

Chia-Nan Wang et al. [2] assessed cyber security in the US market using the EBM-DEA model. The study analyzed both the input and the output variables of cybersecurity businesses efficiency using 2020 financial

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Nguyen Ngoc Hiep and Hoang Minh Tuan are with the Department of Logistics and International Business, Dai Nam University, Hanoi, Vietnam (e-mails: hiepn@dainam.edu.vn and tuanhm@dainam.edu.vn). June Raymond L. Mariano is with Mechanical and Allied Department, Technological University of the Philippines, Manila, Philippines (e-mail: juneraymond_mariano@tup.edu.ph).

* Corresponding author.

data. Pengjun Zhao et al. [3] utilized the EBM DEA model to assess TSCDEE for 30 Chinese provinces from 2010 to 2016. The analysis showed that the transportation sector in the evaluated Chinese regions exhibited a carbon dioxide emissions efficiency of 0.618. This study indicates that TSCDEE is significantly related to urbanization level and urban population density, while transportation structure, traffic infrastructure quality, and technological progress significantly improve it. Huazhu-Zheng et al. [4] investigated the impact of urbanization in China on urban energy eco-efficiency (UEEE) by analyzing data from 271 cities from 2003 to 2020, based on the Meta-frontier Super Epsilon-based Measure (Super-EBM) model with a Tobit model. The study's results demonstrate that UEEE is sustainable yet inefficient in terms of its time frame. These findings reinforce the need to consider local urbanization and technology in policy formulation. Jaclyn A. Card et al. [5] used the EBM model to better understand the differences between online consumers and those who do not purchase travel items. The results indicate that the EBM model efficiently differentiates personal factors between shoppers and non-shoppers, although it is inaccurate in assessing store characteristics. Sulaman-Muhammad et al. [6] utilized Data Envelopment Analysis (DEA) to measure environmental efficiency using two methodologies: Epsilon-Based Measure (EBM) and Slack-Based Measure (SBM).

One fundamental regression method is the Method of Moments Quantile (MMQ) regression. The findings demonstrate that EU nations' total environmental efficiency has increased over time, and that policymakers are becoming more interested in the technology world. Gábor Nagy [7] presented a comprehensive approach for assessing university performance through the application of Data Envelopment Analysis (DEA) and the Analytic Hierarchy Process (AHP). The findings show that institutional efficiency, transparency, and competitiveness are greatly increased when objective indicators and quantitative techniques are combined. Using the Global Malmquist-Luenberger Index, Zheng Yang et al. [8] evaluated the logistics providers' effectiveness in relation to the input and output efficiency of the majority of businesses. Shraddha Mishra [9] evaluated the effectiveness of fourteen distribution hubs of a logistics company using DEA and MDEA. This paper provides methods for enhancing non-ideal hub performance. Beilei Wang et al. [10] employed the super-efficiency SBM model to analyze the efficiency levels of neighboring regions, showing that volatility in neighborhood efficiency impacted the model's temporal and geographic evolution characteristics. Using DEA-BCC and geographical analysis, Locaitienė, V., & Čiziūnienė, K. [11] evaluated the modifications in logistics efficiency of 15 major ports in the Baltic Sea region from 2019 to 2023, including the infrastructure and technological issues affecting port performance. Considering the overall framework of sustainable and efficient development, Linlin Cui et al. [12] utilized DEA models to assess the operational efficiency of ports in China. The method will identify inefficiencies, improve production, and optimize resource allocation. Singh, A., & Gundimeda, H. [13]

applied data envelopment analysis (DEA) to assess the efficiency of organizations in the Indian leather market. Chia-Nan Wang et al. [14] developed a hybrid methodology employing the DEA Malmquist and Epsilon-Based Measure (EBM) models to evaluate the performance of seaport terminal operators in Vietnam.

The researchers investigated efficiency improvements from 2015 to 2020 and found that this integrated methodology provides a useful tool for benchmarking within the maritime industry, which provides useful information for managers that would strengthen operational performance. Chia-Nan Wang et al. [15] proposed a two-stage DEA framework for assessing the efficiency of major ports in Vietnam, distinguishing between production and service components of their operations. The main result indicated that overall port efficiency was not ideal, with improvements primarily attributed to technical modifications rather than to innovative technology. The result showed the importance for port managers to focus on improving commercial and customer service strategies to improve overall efficiency. Qiang Cui and Ye Li [16] established a Dynamic Epsilon-Based Measure (DEBM) method for evaluating the dynamic efficiency of 19 airlines from 2009 to 2014. The study successfully identified benchmarking airlines and proved the influence of external economic changes on operational performance through the inclusion of capital stock as a dynamic factor.

Adnan Abbas et al. [17] developed an approach with two phases that combines the EBM model with Tobit regression to analyze the economic and environmental inefficiencies of sunflower farmers in Pakistan. The data indicated significant inefficiencies and showed that factors like formal education and access to extension services considerably enhanced farmers' performance. Nur Annisa Ezzaty Rusli et al. [18] applied a hybrid framework that incorporates the EBM model and Malmquist Index to evaluate the performance of 15 Malaysian logistics companies from 2010 to 2020 in an assessment of the impacts of the COVID-19 pandemic. The numbers indicated that the industry was able to bounce back and make progress in output despite the difficulties it faced during the early stages of the pandemic on every continent.

2.2. Methodology

(a) *Epsilon-based measure efficiency*: Technical efficiency metrics utilized by DEA are classified into radial and non-radial measurements. The radial measurement takes into account any slack and simply reports the corresponding variation in input or output. However, the non-radial measurement directly addresses slacks without consideration for the variations in the proportion of inputs and outputs. Thus, in some instances, both may lead to an inappropriate evaluation. The EBM model was created to address this problem. The model integrates both radial and non-radial characteristics. The two parameters in this framework—one scalar and one vector—are defined by the affinity index about the inputs and outputs. The radial and non-radial models are integrated into a singular model for evaluating decision marketing units (DMU) efficiency utilizing these two variables.

Table 1. List of DMUs.

No	Name company	DMU
1	UPS	LO-01
2	DHL	LO-02
3	JD Logistics	LO-03
4	SF Express	LO-04
5	Meituan	LO-05
6	ZTO Express	LO-06
7	PostNL N.V	LO-07
8	Aramex PJSC	LO-08
9	C.H. Robinson Worldwide	LO-09

By showing that the EBM is input-oriented (EBM I-C) for $DMU_0 = (x_0, y_0)$, subsequently compute it as

$$\gamma^* = \min_{\theta, \lambda, s^-} \theta - \varepsilon_x \sum_{i=1}^s \frac{w_i^- s_i^-}{x_{i0}} \quad (1)$$

This is subject to

$$\theta x_0 - X\lambda - s^- = 0 \quad (2)$$

$$Y\lambda \geq y_0, \lambda \geq 0, s^- \geq 0 \quad (3)$$

where, the weight (relative importance) of input (i) is w_i^- and $\sum_{i=1}^s w_i^- = 1$ ($w_i^- \geq 0 \forall i$) and ε_x is the parameter that integrates the radial θ and nonradial slacks terms.

(b) *Diversity index and affinity index*: Because it makes the relationship between two variables clearer, Pearson's correlation is significant in the DEA. It creates a correlation estimate from the raw data. A high Pearson index suggests a relationship between the two variables. Conversely, a skewed input-output relationship is indicated by a low correlation coefficient. The value of Pearson's correlation coefficient ranges from -1 to $+1$.

In addition, weight serves as a critical factor in a DEA. The relationship between input and output is governed by the weight [51]. A weight near zero signifies that variations in the input do not influence the output. Positive weights indicate an inverse relationship between input and output; in particular, an increase in input corresponds to a decrease in output.

The parameters of ε_x and w_i significantly influence the efficiency assessment of the DMUs within the EBM model. The EBM model will utilize the affinity index between two vectors instead of employing the Pearson's correlation coefficient as a model.

Let $a \in R_+^n$ and $b \in R_+^n$ be two non-negative vectors with a dimension n . The values validated for a particular input component in DMUs are presented. $S(a, b)$ represents the affinity index between vectors, which includes the following parameters:

$$S(a, a) = 1 \quad (4)$$

is identical with arbitrary a , and

$$S(a, b) = S(b, a) \quad (5)$$

Table 2. Data of delivery service company.

a. Years 2021–2022.

2021 (Currency Unit: USD)				
DMU	(I) Total asset	(I) Liabilities	(O) Gross profit	(O) Revenue
UPS	69,405,000	55,136,000	20,280,000	97,287,000
DHL	63,592,000	44,093,000	14,503,000	81,747,000
JD Logistics	76,795,068	36,405,935	5,784,076	104,693,402
SF Express	209,899,982	111,984,735	25,638,140	207,186,647
Meituan	240,853,269	115,096,507	42,474,128	179,127,997
ZTO Express	62,772,343	13,844,762	6,589,377	30,405,839
PostNL N.V	2,484,000	2,055,000	697,000	3,466,000
Aramex PJSC	5,399,948	2,723,955	1,430,867	6,068,805
C.H. Robinson Worldwide, Inc	7,028,112	5,006,178	1,608,479	23,102,138
2022 (Currency Unit USD)				
DMU	(I) Total Asset	(I) Liabilities	(O) Gross profit	(O) Revenue
UPS	71,124,000	51,321,000	21,014,000	100,338,000
DHL	68,476,000	44,758,000	15,521,000	94,436,000
JD Logistics	106,697,271	53,488,710	10,099,637	137,402,008
SF Express	216,842,707	118,556,658	33,418,054	267,490,414
Meituan	244,481,192	115,775,475	61,752,979	219,954,948
ZTO Express	78,523,586	24,051,116	9,039,275	35,376,996
PostNL N.V	2,221,000	2,042,000	487,000	3,145,000
Aramex PJSC	6,092,509	3,574,121	1,424,304	5,926,005
C.H. Robinson Worldwide, Inc	5,954,564	4,601,142	1,870,197	24,696,625

is symmetric, and

$$S(a, b) = S(b, a) \quad (6)$$

for every $t > 0$ is units-invariant, and

$$1 \geq S(a, b) \geq 0 \quad (7)$$

for arbitrary a and b .

$$1 \geq S(a, b) \geq 0 / (\forall a, b) \quad (8)$$

Table 2. Data of delivery service company (2021–2024).

b. Years 2023–2024.

2023 (Currency Unit USD)				
DMU	(I) Total asset	(I) Liabilities	(O) Gross profit	(O) Revenue
UPS	70,857,000	53,543,000	17,238,000	90,958,000
DHL	66,830,000	43,942,000	13,096,000	81,758,000
JD Logistics	112,901,717	57,528,082	12,683,157	166,624,712
SF Express	221,490,655	118,206,995	33,135,570	258,409,403
Meituan	293,029,632	141,073,265	97,191,161	276,744,954
ZTO Express	88,465,221	28,184,813	9,662,526	38,418,915
PostNL N.V	2,180,000	1,980,000	440,000	3,165,000
Aramex PJSC	5,827,840	3,359,920	1,426,929	5,694,022
C.H. Robinson Worldwide, Inc	5,225,280	3,806,583	1,138,873	17,596,443
2024 (Currency Unit USD)				
DMU	(I) Total Asset	(I) Liabilities	(O) Gross profit	(O) Revenue
UPS	70,070,000	53,327,000	16,356,000	91,070,000
DHL	69,875,000	45,665,000	13,154,000	84,186,000
JD Logistics	117,867,788	54,900,868	18,698,413	182,837,584
SF Express	213,824,213	111,488,992	39,610,272	284,420,059
Meituan	324,354,917	151,750,839	129,784,594	337,591,576
ZTO Express	92,340,330	29,665,497	13,717,092	44,280,720
PostNL N.V	2,120,000	1,915,000	402,000	3,252,000
Aramex PJSC	5,725,621	3,202,040	1,512,203	6,324,444
C.H. Robinson Worldwide, Inc	5,297,926	3,575,875	1,308,765	17,724,956

Let us define

$$c_j = \ln \frac{b_j}{a_j} = (j = 1, \dots, n) \quad (9)$$

$$\bar{c} = \frac{1}{n} \sum_{j=1}^n c_j \quad (10)$$

$$c_{\max} = \max_j \{c_j\} \quad (11)$$

$$c_{\min} = \min_j \{c_j\} \quad (12)$$

The diversity index of vectors (a, b) will be calculated as the divergence of $\{c_j\}$ from the average $\bar{c}$ as

$$D(a, b) = \frac{\sum_{j=1}^n |c_j - \bar{c}|}{n(c_{\max} - c_{\min})} = 0 \text{ if } c_{\max} = c_{\min} \quad (13)$$

with $0 \leq D(a, b) = D(b, a) \leq \frac{1}{2}$. $D(a, b) = 0$ only if vector a and vector b are proportional.

If we denote the affinity index between vector a and vector b as $S(a, b)$ then

$$S(a, b) = 1 - 2D(a, b) \quad (14)$$

If $1 \geq S(a, b) \geq 0$, $S(a, b)$ is accomplished with properties (7) and (8).

The Pearson's correlation coefficient $P(a, b)$ in DEA is determined using the equation

$$P(a, b) = \frac{\sum_{j=1}^n (a_j - \bar{a})(b_j - \bar{b})}{\sqrt{\sum_{j=1}^n (a_j - \bar{a})^2 \sum_{j=1}^n (b_j - \bar{b})^2}} \quad (15)$$

where, $\bar{a}$ and $\bar{b}$ are the average of a_j and b_j , respectively.

However, the EBM model will use the affinity index in place of Pearson's correlation $P(a, b)$. This corresponds to the range of Pearson's index range is $-1 \leq P(a, b) \leq 1$. Therefore, while evaluating the basic factor, there is no assurance that the primary vector would only have positive components. It will thus be set to $0 \leq P(a, b) \leq 1$.

3. RESULT AND DISCUSSION

3.1. Selection of DMUs

The efficiency scores of DMUs were determined in this work using the EBM model, and validity checks were performed prior to application utilizing indices like diversity and affinity. The delivery service providers chosen by the authors varied in size from DMUs. Table 1 lists the nine delivery service firms that were chosen for the study.

3.2. Research data

As indicated in Table 2, the study's data came from finance Yahoo and the yearly reports found on these delivery service firms' official websites between 2021 and 2024. Two crucial elements in assessing DMU performance using the EBM-DEA technique are input and output. According to earlier relevant research, the authors view gross profit and revenue as the output and total assets and liabilities as the input.

Table 3. Coefficients of correlation between variables (2021–2024).

Year	Factor	Total asset	Liabilities	Gross profit	Revenue
2021	Total Asset	1	0.970105389	0.924720686	0.944505371
	Liabilities	0.970105389	1	0.943846519	0.977084797
	Gross profit	0.924720686	0.943846519	1	0.86598168
	Revenue	0.944505371	0.977084797	0.86598168	1
2022	Total Asset	1	0.978037007	0.920611235	0.95033531
	Liabilities	0.978037007	1	0.908238889	0.985966284
	Gross profit	0.920611235	0.908238889	1	0.836967874
	Revenue	0.95033531	0.985966284	0.836967874	1
2023	Total Asset	1	0.981553807	0.906193734	0.959039075
	Liabilities	0.981553807	1	0.883385534	0.979463913
	Gross profit	0.906193734	0.883385534	1	0.820557325
	Revenue	0.959039075	0.979463913	0.820557325	1
2024	Total Asset	1	0.981469273	0.9286991	0.963235556
	Liabilities	0.981469273	1	0.902064368	0.974632899
	Gross profit	0.9286991	0.902064368	1	0.848952921
	Revenue	0.963235556	0.974632899	0.848952921	1

Table 4. Diversity matrix in the EBM model (2021–2024)

Period		Total asset	Liabilities
2021	Total Asset	0	0.22811
	Liabilities	0.22811	0
2022	Total Asset	0	0.28177
	Liabilities	0.28177	0
2023	Total Asset	0	0.30087
	Liabilities	0.30087	0
2024	Total Asset	0	0.24868
	Liabilities	0.24868	0

3.3. Result and discussion

Before using the EBM model, the Pearson Correlation Coefficient is computed to confirm that the input and output variables are correlated. The Person correlation test results are displayed below in Table 4. These are considered to have a positive connection when the coefficient falls between 0.8 and 1.

The input-oriented model with continuous returns to scale (EBM–I–C) is used in the study to evaluate the performance of nine delivery services companies between 2021 and 2024. Diversity values in Table 5

Table 5. Affinity matrix in EBM model (2021–2022).

Period		Total asset	Liabilities
2021	Total Asset	1	0.54378
	Liabilities	0.54378	1
2022	Total Asset	1	0.43646
	Liabilities	0.43646	1
2023	Total Asset	1	0.54378
	Liabilities	0.54378	1
2024	Total Asset	1	0.50265
	Liabilities	0.50265	1

Table 6. Efficiency scores of the EBM model.

DMU	2021	2022	2023	2024
UPS	1	0.973281	0.740271	0.633452
DHL	0.827323	0.782673	0.646957	0.552158
JD Logistics	0.575619	0.431222	0.607008	0.700205
SF Express	0.528899	0.590568	0.593567	0.631707
Meituan	0.694086	1	1	1
ZTO Express	0.806641	0.639345	0.492193	0.532918
PostNL N.V	0.95591	0.666754	0.642624	0.568697
Aramex PJSC	1	0.847542	0.747906	0.704172
C.H. Robinson Worldwide	1	1	1	1

range from 0 to 0.22811, indicating that the input and output variables satisfy all necessary requirements.

The affinity index between the two vectors is used in place of the affinity index–determined coefficient. When evaluating DMU efficiency inside the EBM paradigm, the affinity index aids in confirming that input and output are acceptable. Affinity values in Table 6 range from 0.43646 to 1, indicating that both the input and output variables satisfy all necessary requirements.

The EBM score for every DMU is determined in part by the input/output weight and epsilon. The weighted index is used to compute the input–output ratio. Table 8's findings demonstrate that every weight and epsilon index has a positive value, suggesting that adjustments to input and output will have a direct impact on output. When assessing the effectiveness of DMUs that meet these requirements, the correction factor epsilon, which has a range of 0 to 1, is employed to guarantee that the input and output data are genuine and meet the model's requirements.

The efficiency ratings and rankings of the nine delivery service providers over time are displayed in Table 8 and Fig. 1. The two units with the best and most

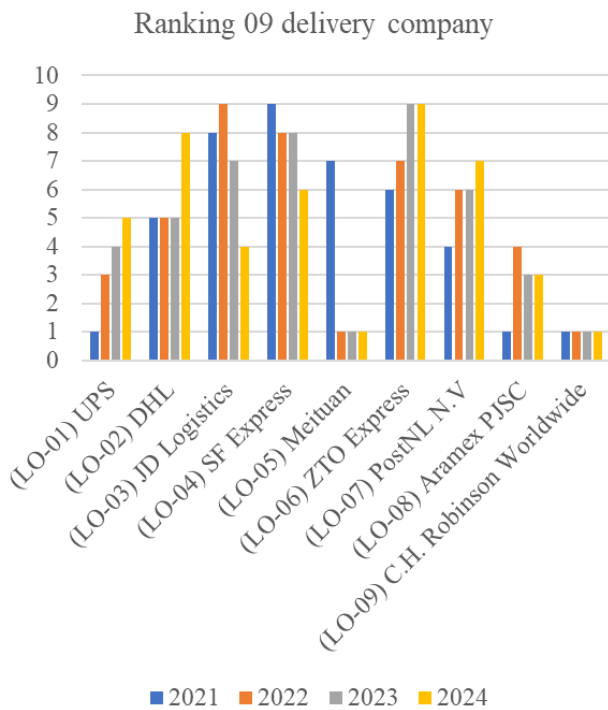


Fig. 1. The efficiency of score of DMUs.

consistent performance in 2021–2024 are LO–05 (Meituan) and LO–09 (C.H. Robinson Worldwide), according to Table 8 and Figure 1. During the period, LO–09 (C.H. Robinson Worldwide) maintained optimal performance (equal to 1). Over the course of the three years, LO–05 (Meituan) continued to hold the second spot.

In addition, LO–01 (UPS), LO–02 (DHL), and LO–08 (Aramex PJSC) all demonstrated improved performance but did not sustain stability. Initially, JD Logistics' LO–03 showed low efficiency, resulting in an overall decrease in 2021; yet, it displayed significant enhancements in 2023 and 2024.

The study showed that although many LOs exhibit uniform efficiency over time, others reveal significant changes or improvements. The ranking shift indicates the different levels of adaptability and competitiveness of each unit found within the work environment.

4. CONCLUSION AND RESEARCH IMPLICATIONS

This study analyzes the performance of nine courier service companies from 2021 to 2024, establishing a framework for managers, investors, and policymakers to further improve the industry's performance.

The primary contributions of the study are as follows:

(1) The outcome assesses the performance of delivery services companies in 2021–2024 using the EBM model. The findings of the analysis show how delivery services firms performed between 2021 and 2024.

(2) The study provides an efficiency image of courier service providers from the past. In the future, courier services will be supported by an understanding of their operational procedures and strategic expansion to carry out a profitable business plan.

(3) In order to select the most appropriate delivery service providers, customers also have a thorough overview of courier service providers.

There are still restrictions even though this study examines the effectiveness of courier service providers. First, in order for future research to develop more models to rank, the study just asks us to characterize efficiency and inefficiency without evaluating delivery service businesses. Second, there may not be enough information available in the reported input and output variables—such as employee capitalization—to examine the operation process. Therefore, these aspects will be further investigated in the upcoming study.

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