Supporting Better Decision-Making: A Combined Grey Model and Data Envelopment Analysis for Efficiency Evaluation in E-Commerce Marketplaces

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Abstract: E-commerce has become an integral part of businesses for decades in the modern world, and this has been exceptionally speeded up during the coronavirus era. To help businesses understand their current and future performance, which can help them survive and thrive in the world of e-commerce, this paper proposes a hybrid approach that conducts performance prediction and evaluation of the e-commerce industry by combining the Grey model, i.e., GM (1, 1) and data envelopment analysis, i.e., the Malmquist-I-C model. For each e-commerce company, GM (1, 1) is applied to predict future values for the period 2020–2022 and Malmquist-I-C is applied to calculate the efficiency score based on output variables such as revenue and gross profit and input variables such as assets, liabilities, and equity. The top 10 e-commerce companies in the US market are used to demonstrate model effectiveness. For the entire research period of 2016–2022, the most productive e-commerce marketplace on average was eBay, followed by Best Buy and Lowe’s; meanwhile, Groupon was the worst-performing e-commerce business during the studied period. Moreover, as most e-commerce companies have progressed in technological development, the results show that the determinants for productivity growth are the technical efficiency change indexes. That means, although focusing on technology development is the key to e-commerce success, companies should make better efforts to maximize their resources such as labor, material and equipment supplies, and capital. This paper offers decision-makers significant material for evaluating and improving their business performance.

Keywords: e-commerce; Malmquist-I-C; GM (1, 1); performance; efficiency; prediction; evaluation; decision making

1. Introduction

Electronic commerce (e-commerce) is thriving in every corner of the world nowadays as purchasing goods and services online has become a common practice among many people because of its convenience. In 2019, an astounding 1.92 billion people shopped online [1]. Amid the Covid-19 online sales boom, the e-commerce industry has accelerated to the forefront of the global retail framework. Increasing from 16.07 billion visits worldwide (January 2020), with exceptionally high demand for everyday goods such as groceries, clothes, and retail tech products, global retail e-commerce traffic reached a
record 22 billion visits in June 2020 [2]. In 2021, the number of digital buyers will be continuously growing, with over 2.14 billion people worldwide expected to shop online [3].

More and more companies around the world have expanded in e-commerce. Many e-commerce businesses are using customized technologies to give customers a personalized experience. Considering the widespread success of many e-commerce brands, it is undisputed that the United States (US) is a notable leader in the global e-commerce sector. The US is presently the second largest e-commerce market in the world after having dominated the world of e-commerce for more than a decade, with annual online sales of 340 billion US dollars [4], placing it ahead of the United Kingdom and behind China. Driven by e-commerce giants such as Amazon and eBay, the US is seeing this market flourish in all sectors and has become the innovation house of new e-commerce trends for the most part. Remarkably, Amazon’s net sales skyrocketed, increasing 40% to 88.91 billion US dollars in the second quarter of 2020, compared with 63.4 billion in the 2nd quarter in 2019 [5]. While the mass furloughs and layoffs began across many countries in the Covid-19 era, Amazon announced they were to hire 100,000 workers to meet surging demand. The company is built on a previously successful model, leveraging its already best-in-class online delivery system to offer a next-day nationwide delivery feature (Prime) [6]. Walmart has outstripped eBay in e-commerce sales for the first time as a result of leveraging digitally native brands, advanced website and app experience, successful click-and-collect operations, and more dynamic delivery times. First-rate merchandising, expedited online delivery, and curbside pickup capability have led Target to join the ranks of the leading e-commerce retail companies in 2020 [7], reporting a total sale of 42.07 billion US dollars for the first six months of the fiscal year [8]. By the end of 2020, with a forecast market share of 39%, Amazon is the biggest e-commerce player by leaps and bounds. Next in line is Walmart, with a 5.3% market share, followed by eBay (4.7%), Best Buy (1.3%), and Costco (1.2%), to name just a few [9].

Technological advances have had an enormous impact on the world of e-commerce, transforming the way digital customers interact with brands and helping them to shop more cost-effectively. These transformations open new opportunities for online businesses and speed up the pace of industry growth. Over the past few years, some of the most emerging and notable technological innovations that have shaped the future of the online shopping experience and driven forward e-commerce success are as follows: big data analytics, machine learning, and artificial intelligence (AI) [10], AI-powered chatbots and voice assistant applications [11], electronic wallets [12], blockchain technology [13], and cognitive supply chain management [14], to name a few. These innovations have led to a vigorous race for technology between all giants in the e-commerce industry. Moreover, effective technical performance and some key factors in e-commerce success, such as regulation of product pricing, maintenance of high-quality products, security, fast and affordable shipping options, to name a few, should be persistently determined.

Many notable studies have looked into e-commerce recently and have provided significant material for businesses in terms of both technical and technological e-commerce advancements. Ijaz et al. [15] emphasized the important role of virtual stores of retail businesses. A virtual store is an online store that offers a checklist of merchandisers and an order form. The paper aimed at selecting a distinct layout that can be used in digital signage. The results indicated that enhancement in the quality and utility of virtual store layouts help boost the revenue of businesses as the customer’s relationship with the retailer will become stronger. Information systems and consumer behavior are found to be the most influencing factors for online shopping [16,17]. Many studies’ findings are useful guidelines for retailers and e-businesses to enhance their service quality and customers’ online shopping experiences. For example, a unified information system–consumer behavior model was developed in [18] to measure some highly influencing factors to online shopping processes. To extract and utilize information from customer behavior, Alfian et al. [19] utilized real-time data processing and the association rule for digital-signage-based online stores. Wagner et al. [20] identified and classified the multiplicity of devices and the diversity of e-channel touchpoints now used for online purchases. Atmosphere cues, such as colors and music, are found to have significant impacts on
emotional responses and behavioral intention, as presented in an experimental study of online stores in [21], which proposed an efficient online store environment that results in more time spent in-store, repurchasing, and revisiting. During the pandemic, more consumers are turning to electronic shopping, which indicates that the accumulation of demand for niche products could be ever-increasing. As an example of the shift to online food shopping services, the investigation of mechanisms in the study of Chang and Meyerhoefer [22] found that sales were highly receptive to Covid-19 in terms of media coverage and online content. The authors presented an empirical study that focused on measuring how online shopping relates to the number of Covid-19 cases in an individual’s local area. With reference to the severe impacts of the Covid-19 pandemic on business activities, Tran [23] presented a systematic approach to investigate the effect of the perceived effectiveness of e-commerce platforms on consumers’ perceived economic benefits in forecasting sustainable consumption.

This paper proposes an integrated model combining GM (1, 1) and Malmquist-I-C models in a data envelopment analysis (DEA) in order to measure and predict, from 2016 to 2022, the technical efficiency and frontier-shift (technological change) of the 10 largest e-commerce marketplaces in the US that have had, and continue to have, an enormous influence on global online selling. The Grey prediction model is used to produce potential metrics, which are considered key performance measurements that describe how a company is successfully achieving its goals; they are necessary data for businesses to make strategic production plans and be prepared for numerous difficult circumstances. Malmquist-I-C is applied to calculate technical efficiency and technological change and the overall productivity growth of the companies for the period 2016–2022. This paper aims to provide comprehensive insights into e-commerce companies to evaluate their historical, current, and future overall performance compared with other rivals, especially in the Covid-19 era, since it has been found that the pandemic has given a major boost to this industry. To the best of our knowledge, there has not been a combination of these forecasting models, i.e., GM (1, 1) and DEA, to evaluate and predict the performance of e-commerce companies. The managerial implications of this paper can help businesses improve their decision-making processes and find out key success factors in order to harness and enhance e-commerce for sustainable development.

This paper is structured as follows. A review of relevant studies is shown in Part 2. Part 3 gives a short discussion of the Grey model and data envelopment analysis. Part 4 discusses the analysis of the results. Discussion, conclusion, and limitations of the paper are shown in Part 5.

2. Literature Review

2.1. Grey Model

First introduced in 1982 by Deng [24], the Grey model has become a very popular method for solving uncertain problems with rare and incomplete data; as an advantage over traditional statistical models, it can address problems with a small number of data to predict the behavior of an unknown system [25]. In most studies, the Grey model is presented as GM (m, n), where m is the order, and n is the number of variables in the modeling equation. GM (1, 1) is the simplest model and most widely proposed as a useful forecasting model in many areas, such as day trading stock price [26], the optic–electronics industry [27], and the high-tech industry [28]. To increase the accuracy of Grey prediction models, an improved data modeling approach is discussed in [29], in which Grey models are advanced to determine the interaction between an input–output process, ambiguous internal relationships, unknown processes, and inadequate information. In fuzzy GM (1, 1), which considers fuzzy inputs as developed data [30], the relationship between GM (1, 1) and the fuzzy dataset is built such that when the system is unpredictable and vague, the fuzzy GM (1, 1) can be applied to predict the likely future trend. The relationship between the fuzzy method and the Grey model from the study had a fundamental link to robust methods of short-term forecasting to solve the forecasting problem.
2.2. Data Envelopment Analysis (DEA)

This research employs the DEA Malmquist productivity index to measure the productivity changes over time and to get insight into the sources of its transformation, i.e., developed by Fare et al. [31,32]. DEA is linear programming (LP)-based technique that is used for the performance evaluation of decision-making units (DMUs). This method has successfully been used in many applications such as education, banking, aviation, and energy sustainability, to name just a few. For example, Briec et al. analyzed productivity growth and the nature of technical change for a case study of Portuguese hydroelectric-generating plants [33]. The authors used the Malmquist productivity index for a comparative purpose. There seems to have been a global transformation from the implementation of the decomposition of technological change to the frontier of best practice; this is the overall catalyst of technical change. Romano and Guerrini applied DEA to measure and compare water utility companies’ performance, concluding varying degrees of importance that had significant effects on water use [34]. Merkert and Hensher [35] proposed a two-stage DEA methodology to evaluate key system measurements of passenger airlines and find out some key factors that have major impacts on all three phases of airline efficiency: technological, allocative, and, eventually, cost-effectiveness. For the hi-tech industry, Qazi and Yulin used the Malmquist productivity index to identify the sources of its growth [36]. Not only applying DEA to one single industry, Lee et al. measured capabilities among many industries in South Korea in terms of patent applications and suggested some strategies to make it possible for weak industries to become stronger, emphasizing that the importance of patents as a way of defending and improving technology and competitiveness has been increased by global competition [37].

2.3. Methodology Motivation

Some of the widely used methodologies to assess e-businesses’ performance or related firms are summarized in Table 1. Typical key system measurements that are ranked or evaluated are financial performance [38], supply chain integration [39], website performance [40–43], cost efficiency [44,45], productivity effects [46–48], technical and technological efficiency [49–55], security [56], and success factors [57], to name just a few. In terms of methodologies, the potential and strengths of DEA in e-commerce performance evaluation are highlighted in many studies. CCR (Charnes–Cooper–Rhodes) and BCC (Banker–Charnes–Cooper) are basic models of DEA. The CCR model identifies the overall inefficiency, while the BCC model differentiates between technical efficiency and scale efficiency, as discussed in [48,51,52,58–60]. In order to discriminate the performance among efficient DMUs, a super slack-based measure (super SBM), based on the traditional DEA model, was applied in [38,54,55]. Developed by Tone [61], the super SBM model can not only obtain a complete ranking of effective DMUs but also eliminates the slack problem, further optimizes the shortcomings, and shows a more accurate metric. The DEA Malmquist model is an extension of the original DEA model that divides total productivity change into technical efficiency change and technological efficiency change, as proposed in [46,50,53]. Some other methodologies that are widely used for the evaluation of e-commerce impact on business efficiency include the model of cost efficiency [45,47,62,63], the regression model [39,44,48,49,51,52], the analytical hierarchy process (AHP), and the technique for order of preference by similarity to ideal solution (TOPSIS) and/or under fuzzy conditions [41–43]. From our literature review, a hybrid approach that combines the forecasting model GM (1, 1) and DEA Malmquist to predict and evaluate the performance of e-commerce companies has never been reported. This lack attracted our attention. Therefore, this paper aims to provide an evaluation method for businesses to find out key factors, drawbacks, and opportunities that affect their success in the e-commerce industry.
| No. | Authors                  | Year | DEA CCR | DEA BCC | DEA Super SBM | DEA Malmquist | Cost Efficiency | Regression Model | (Fuzzy) AHP | (Fuzzy) TOPSIS |
|-----|--------------------------|------|---------|---------|---------------|---------------|-----------------|-----------------|-------------|---------------|
| 1   | Donthu and Yoo [48]      | 1998 | x       |         |               |               |                 |                 |             |               |
| 2   | Ashton et al. [45]       | 2001 |         | x       |               |               |                 |                 |             |               |
| 3   | Ratchford [47]           | 2003 |         | x       |               |               |                 |                 |             |               |
| 4   | Chen et al. [38]         | 2004 |         |         |               |               |                 |                 |             |               |
| 5   | Kong et al. [57]         | 2005 |         |         |               |               |                 |                 | x           |               |
| 6   | Barros [51]              | 2006 | x       |         |               |               |                 |                 |             |               |
| 7   | Perrigot and Barros [52] | 2008 | x       | x       |               |               |                 |                 |             |               |
| 8   | Baršauskas et al. [62]   | 2008 |         |         |               |               |                 |                 |             |               |
| 9   | Ho et al. [63]           | 2009 |         |         |               |               |                 |                 |             |               |
| 10  | Iyer et al. [39]         | 2009 |         |         |               |               |                 |                 | x           |               |
| 11  | Yu and Ramanathan [50]   | 2009 |         |         |               |               |                 |                 |             |               |
| 12  | Ho [58]                  | 2011 | x       |         |               |               |                 |                 |             |               |
| 13  | Yu et al. [41]           | 2011 |         | x       |               |               |                 |                 |             |               |
| 14  | Zhang et al. [56]        | 2012 |         |         |               |               |                 |                 |             |               |
| 15  | Yang et al. [59]         | 2014 | x       |         |               |               |                 |                 |             |               |
| 16  | Zhou et al. [49]         | 2014 |         |         |               |               |                 |                 |             |               |
| 17  | Yang et al. [60]         | 2016 | x       |         |               |               |                 |                 |             |               |
| 18  | Grüsschow et al. [44]    | 2016 |         |         |               |               |                 |                 |             |               |
| 19  | Shao and Lin [33]        | 2016 |         |         |               |               |                 |                 |             |               |
| 20  | Kang et al. [42]         | 2016 |         |         |               |               |                 |                 | x           |               |
| 21  | Yang et al. [46]         | 2017 |         |         |               |               |                 |                 |             |               |
| 22  | Aggarwal and Aakash [43] | 2018 |         | x       |               |               |                 |                 |             |               |
| 23  | Hongping et al. [55]     | 2018 |         |         |               |               |                 |                 | x           |               |
| 24  | Rouyendegh et al. [40]   | 2019 |         |         |               |               |                 |                 |             |               |
| 25  | Shan et al. [54]         | 2019 |         |         |               |               |                 |                 | x           |               |

Notes: DEA: data envelopment analysis; CCR: Charnes–Cooper–Rhodes; BBC: Banker–Charnes–Cooper; SBM: slack-based measure; AHP: analytical hierarchy process; TOPSIS: technique for order of preference by similarity to ideal solution.

3. Materials and Methods

3.1. Research Framework

This research proposes an integrated model of GM (1, 1) and Malmquist-I-C for operational efficiency prediction and evaluation in the e-commerce industry for the period from 2016 to 2022. The research framework includes three main parts that are presented in Figure 1.
In the first part, the research problem is defined. This paper considers the top 10 e-commerce companies in the US market, which are considered DMUs. Additionally, the inputs and outputs are considered based on their influence on the model approach. Input variables include assets, liabilities, and equity. Revenue and gross profit are considered output variables. The second part describes the integrated model. Firstly, based on historical data (2016–2019), GM (1, 1), and mean absolute percentage error (MAPE) tests are used to predict future values (2020–2022). Then, the Malmquist-I-C model and the Pearson correlation test are used to assess the operational efficiency of 10 DMUs. The last part provides model results, discussions, and recommendations for future studies.

3.2. GM (1, 1) Model

Grey forecasting, GM (1, 1), is very useful in cases where there is a lack of historical data (however, the model requires at least four periods of time of historical data). The process of calculation is presented in Figure 2 below [25,64,65].
The original time-series data $X(0)$, is shown in Equation (1):

$$X(0) = \left[ X(0)(1); X(0)(2); \ldots; X(0)(n) \right], n \geq 4$$ (1)

where $n$ denotes the total historical time period.

We generate $X(1)$ by using the accumulating generation operation (AGO) to eliminate the uncertainties of the original data. Equation (2) shows the equation of AGO:

$$X(1) = \left[ X(1)(1); X(1)(2); \ldots; X(1)(n) \right], n \geq 4$$ (2)

where

$$X(1)(1) = X(0)(1)$$

$$X(1)(k) = \sum_{i=1}^{k} X(0)(i), k = 1, 2, \ldots, n.$$ (3)

We generate the partial data series $Z(0)$ in Equation (3):

$$Z(1) = \left[ Z(1)(2); Z(1)(3); \ldots; Z(1)(n) \right], n \geq 4$$ (3)

where $Z(1)(k)$ is the value of the mean sequence, as described in Equation (4).

$$Z(1)(k) = \frac{1}{2} \times \left[ X(1)(k) + X(1)(k-1) \right], k = 2, 3, \ldots, n$$ (4)

From $X(1)$ in Equation (2), the first-order differential equation $X(1)(k)$ of GM (1, 1) is built as Equation (5):

$$\frac{dX(1)(k)}{dk} + uX(1)(k) = v$$ (5)

where $u$ denotes the developing coefficient and $v$ denotes the input of GM (1, 1), respectively.

Practically, the value of parameters $u$ and $v$ cannot be computed directly from Equation (5). Therefore, these parameter values can be computed by using the least-square method in Equation (6):

$$\hat{X}(k+1) = \left( X(0)(1) - \frac{v}{u} \right) e^{-uk} + \frac{v}{u}$$ (6)

where $\hat{X}(k+1)$ represents the value of the forecast of $X$ at stage $k+1$. The value of coefficients $[u, v]^T$ can be attained using the ordinary least square (OLS) method, as defined by Equations (7)–(9).

$$\begin{bmatrix} u \\ v \end{bmatrix} = \left( H^T H \right)^{-1} H^T K$$ (7)

$$K = \begin{bmatrix} X(0)(2) \\ X(0)(3) \\ \vdots \\ \vdots \\ X(0)(n) \end{bmatrix}$$ (8)

$$H = \begin{bmatrix} -Z(1)(2) & 1 \\ -Z(1)(3) & 1 \\ \vdots & \vdots \\ \vdots & \vdots \\ -Z(1)(n) & 1 \end{bmatrix}$$ (9)

where $[u, v]^T$ is the parameter series, $K$ is the data series, and $H$ is the data matrix.
From the values of $X$ (k + 1) in Equation (6), set $X$ becomes the forecasted series in Equation (10):

$$X = \begin{bmatrix} X^{(0)}(1) ; X^{(0)}(2) ; \ldots ; X^{(0)}(n) \end{bmatrix}$$ (10)

where $X^{(0)}(1) = X^{(0)}(1)$.

Applying the inverse-accumulated generation operation, Equation (11) is attained as follows:

$$X^{(0)}(k + 1) = \left( X^{(0)}(1) - \frac{p}{u} \right) e^{-uk} (1 - e^u)$$ (11)

The values of predictive accuracy can be measured using the mean absolute percentage error (MAPE), which is named $\alpha$ [66]. The formula is presented as follows:

$$\alpha = \frac{1}{n} \sum \left( \frac{X^{(0)}(k) - X^{(0)}(k)}{X^{(0)}(k)} \right) \times 100\%$$ (12)

where $\left\{ \begin{array}{ll} \alpha \leq 10\% : & \text{High Accuracy} \\ 10\% < \alpha \leq 20\% : & \text{Good} \\ 20\% < \alpha \leq 50\% : & \text{Reasonable}, \alpha > 50\% : \text{Inaccurate} \end{array} \right.$

### 3.3. Malmquist-I-C Model

The Pearson coefficient (i.e., the isotropic condition) must be tested before using the Malmquist-I-C model [66]. This Pearson coefficient shows the correlation of two factors, where their values range from (-1; 0; +1), presenting the relationship in negative, none, and positive linear relationships, respectively. The DEA model needs data in a positive relationship. The formula of Pearson ($r_{pq}$) is presented as Equation (13) below.

$$r_{pq} = \frac{\sum_{i=1}^{n} p_i q_i - \frac{\sum_{i=1}^{n} p_i \sum_{i=1}^{n} q_i}{n}}{\sqrt{\left( \sum_{i=1}^{n} p_i^2 - \left( \frac{\sum_{i=1}^{n} p_i}{n} \right)^2 \right)^{1/2} \left( \sum_{i=1}^{n} q_i^2 - \left( \frac{\sum_{i=1}^{n} q_i}{n} \right)^2 \right)^{1/2}}}$$ (13)

where $n$ denotes sample size; $p_i, q_i$ denote the locations of individual sample $i$.

In this research, the Malmquist productivity index (MPI) is used for evaluating the operational efficiency of the top e-commerce company in the US for the period 2016–2019. The operational efficiency of the DMUs is measured from period $t$ to period $t+1$, consisting of technical efficiency (i.e., catch-up index, $C_{t\rightarrow t+1}$), technological efficiency (i.e., frontier-shift index, $F_{t}^{t+1}$), and MPI (i.e., $MPI_{t}^{t+1}$), are shown in Equations (14)–(16) [32,67].

$$C_{t\rightarrow t+1} = \frac{O_{Z_{t+1}}}{O_{Z_{t}}} = \frac{TSE_{t+1}}{TSE_{t}}$$ (14)

$$F_{t}^{t+1} = \left[ \frac{O_{Z_{t}}}{O_{Z_{t+1}}} \times \frac{O_{Z_{t+1}}}{O_{Z_{t}}} \right]^{1/2} = \left[ \frac{TSE_{t}}{TSE_{t+1}} \times \frac{IE_{t}^{t+1}}{IE_{t}^{t+1}} \right]^{1/2}$$ (15)

$$MPI_{t}^{t+1} = C_{t\rightarrow t+1} \times F_{t}^{t+1} = \frac{TSE_{t+1}}{TSE_{t}} \times \left[ \frac{TSE_{t}}{TSE_{t+1}} \times \frac{IE_{t}^{t+1}}{IE_{t}^{t+1}} \right]^{1/2}$$ (16)
where
\[
\begin{align*}
Milt_{t+1} &< 1 : \text{decrease in operational efficiency} \\
Milt_{t+1} &= 1 : \text{no change in operational efficiency} \\
Milt_{t+1} &> 1 : \text{increase in operational efficiency}
\end{align*}
\]

4. Empirical Results

4.1. Data Analysis

The selection of inputs and outputs significantly affects the Malmquist model's results [68]. Based on the importance of financial indexes and the list of the used inputs and outputs in previous studies (Table 2), this paper considers three inputs (assets, liabilities, equity) and two outputs (revenue, gross profit), which are used in the proposed model. These index systems for operational efficiency evaluation and prediction in the e-commerce industry are described as follows and can be found in Figure 3.

- (I1) Assets: tangible and intangible assets owned by an e-commerce firm, i.e., properties, equipment.
- (I2) Liabilities: outstanding checks, compensation, current portion of debt, accounts payable.
- (I3) Equity: total tangible and intangible assets minus liabilities.
- (O1) Revenue: income of e-commerce enterprise when they operate the business, i.e., the value of goods and services of their business.
- (O2) Gross profit: profits appear as revenue minus the cost of goods sold. Note that gross profit is not deducted from other fixed and variable expenses, i.e., rent, utilities, payroll.

### Table 2. List of the used inputs and outputs in previous studies.

| No. | Authors       | Year | Inputs                      | Outputs                      | Research Scope          |
|-----|---------------|------|-----------------------------|------------------------------|-------------------------|
| 1   | Wen et al. [69] | 2003 | Web technology, Operating cost, Staffs | Sales, Capital, Capacity, Utilization, Site quality | E-commerce, 12 DMUs     |
| 2   | Ho and Wu [63] | 2009 | Deposit, Operation cost, Employees, Equipment | Revenue, Daily reach rate | Online banking, 45 DMUs |
| 3   | Lu and Hung [70] | 2011 | Equity, Liability, Employees, Operating expense | Net sales, Net income, Market value, Intangible value | E-retailing, 30 DMUs     |
| 4   | Ho [58]        | 2011 | Assets, Equity, Operating expense, Employees | Revenue, Profit, ROA, ROE   | Internet, 69 DMUs       |
| 5   | Tao et al. [71] | 2013 | Equipment, Operating cost, Employees | Revenue, Web metrics         | E-banking, 32 DMUs      |
| 6   | Yang et al. [59] | 2014 | Costs, Assets, Labors | Revenue, Profit | E-commerce, 25 DMUs |
| 7   | Yang et al. [60] | 2016 | Employees, Operating expenses, Total assets | Revenue, Market share | E-commerce, 35 DMUs |

**Notes:** DMU: decision-making units; ROA: return on assets; ROE: return on equity.
Table 3 presents the list of top 10 e-commerce companies in the US, i.e., 10 DMUs of the paper’s model [72,73], consisting of Amazon, eBay, Walmart, Target, BestBuy, Groupon, Overstock, Costco, Etsy, and Lowe’s. The revenues in 2019 of these DMUs are included. The authors collected historical data of inputs and outputs of these DMUs for the period from 2016–2019 from annual financial statements [74]. The statistics description on input and output variables (e.g., maximum, minimum, average, standard deviation) are presented in Table 4.

Table 3. The list of 10 e-commerce companies in the US.

| Number | DMUs  | Company | Code | Revenue in 2019 (Million USD) |
|--------|-------|---------|------|-------------------------------|
| 1      | ECOM01| Amazon  | AMZN | 280,522                       |
| 2      | ECOM02| eBay    | EBAY | 10,800                        |
| 3      | ECOM03| Walmart | WMT  | 514,405                       |
| 4      | ECOM04| Target  | TGT  | 75,356                        |
| 5      | ECOM05| BestBuy | BBY  | 42,879                        |
| 6      | ECOM06| Groupon | GRPN | 2219                          |
| 7      | ECOM07| Overstock| OSTK | 1459                          |
| 8      | ECOM08| Costco  | COST | 152,703                       |
| 9      | ECOM09| Etsy    | ETSY | 818                           |
| 10     | ECOM10| Lowe’s  | LOW  | 71,309                        |

Table 4. Statistics on input and output data (2016–2019).

| Year   | Assets Max | Liabilities Min | Equity Average | Revenue SD | Gross profit SD |
|--------|------------|-----------------|----------------|------------|-----------------|
| 2016   | 199,581    | 83,611          | 83,611         | 482,130    | 121,146         |
|        | 485.08     | 172.96          | 172.96         | 364.97     | 241.64          |
|        | 42,786.76  | 15,153.88       | 15,153.88      | 137,963.47 | 34,189.54       |
|        | 57,388.93  | 23,612.10       | 23,612.10      | 34,189.54  |                 |
| 2017   | 198,825    | 80,535          | 80,535         | 485,873    | 124,617         |
|        | 433.82     | 172.12          | 172.12         | 364.97     | 241.64          |
|        | 48,087.49  | 15,030.29       | 15,030.29      | 137,963.47 | 34,189.54       |
|        | 61,988.78  | 23,164.90       | 23,164.90      | 34,189.54  |                 |
| 2018   | 204,522    | 80,822          | 80,822         | 500,343    | 126,947         |
|        | 461.22     | 210.71          | 210.71         | 603.69     | 353.91          |
|        | 52,116.32  | 16,994.32       | 16,994.32      | 107,236.30 | 37,264.74       |
|        | 68,007.85  | 24,639.66       | 24,639.66      | 37,264.74  |                 |
| 2019   | 225,248    | 79,634          | 79,634         | 514,405    | 129,104         |
|        | 417.73     | 177.86          | 177.86         | 603.69     | 353.91          |
|        | 60,006.28  | 17,937.45       | 17,937.45      | 115,247.07 | 30,917.96       |
|        | 82,608.74  | 27,163.90       | 27,163.90      | 39,347.58  |                 |

Unit: million USD.
4.2. Results of GM (1, 1)

In this paper, the Grey forecasting model, GM (1, 1), is used to predict the future value of DMUs (2020–2022) based on historical data (2016–2019). Table 5 shows the data collection of input and output variables for the period from 2016 to 2019 of ECOM01-Amazon. The following procedures present an example of the calculation of ECOM01-Amazon, e.g., (I) Assets; other variables are calculated using the same methodology.

| ECOM01 | Assets | Liabilities | Equity | Revenue | Gross Profit |
|--------|--------|-------------|--------|---------|--------------|
| 2016   | 83,402 | 64,117      | 19,285 | 135,987 | 30,103       |
| 2017   | 131,310| 103,601     | 27,709 | 177,866 | 40,683       |
| 2018   | 162,648| 119,099     | 43,549 | 232,887 | 59,704       |
| 2019   | 225,248| 163,188     | 62,060 | 280,522 | 74,754       |

Unit: million USD.

**Step 1:** Input original time-series data $X^{(0)}$, Equation (1).

$$X^{(0)} = (X^{(0)}(1); X^{(0)}(2); X^{(0)}(3); X^{(0)}(4)) = (83,402; 131,310; 162,648; 225,248)$$

**Step 2:** Generate time-series data $X^{(1)}$ from $X^{(0)}$, Equation (2).

$$X^{(1)} = (X^{(1)}(1); X^{(1)}(2); X^{(1)}(3); X^{(1)}(4)) = (83,402; 214,712; 377,360; 602,608)$$

where

- $X^{(1)}(1) = X^{(0)}(1) = 83,402$
- $X^{(1)}(2) = X^{(0)}(1) + X^{(0)}(2) = 214,712$
- $X^{(1)}(3) = X^{(0)}(1) + X^{(0)}(2) + X^{(0)}(3) = 377,360$
- $X^{(1)}(4) = X^{(0)}(1) + X^{(0)}(2) + X^{(0)}(3) + X^{(0)}(4) = 602,608$

**Step 3:** Generate partial series data $Z^{(1)}$ from $X^{(1)}$, Equations (3) and (4).

$$Z^{(1)}(1) = X^{(0)}(1) = 83,402$$
$$Z^{(1)}(2) = \frac{1}{2}(83,402 + 214,712) = 149,057$$
$$Z^{(1)}(3) = \frac{1}{2}(214,712 + 377,360) = 296,036$$
$$Z^{(1)}(4) = \frac{1}{2}(377,360 + 602,608) = 489,984$$

Hence, $Z^{(1)} = (Z^{(1)}(2); Z^{(1)}(3); Z^{(1)}(4)) = (149,057; 296,036; 489,984)$

**Step 4:** Calculate coefficient $u$ and Grey input $v$, Equations (5)–(9).

$$K = \begin{bmatrix} X^{(0)}(2) \\ X^{(0)}(3) \\ X^{(0)}(4) \end{bmatrix} = \begin{bmatrix} 131,310 \\ 162,648 \\ 225,248 \end{bmatrix}$$

$$H = \begin{bmatrix} -Z^{(1)}(2) & 1 \\ -Z^{(1)}(3) & 1 \\ -Z^{(1)}(4) & 1 \end{bmatrix} = \begin{bmatrix} -149,057 & 1 \\ -296,036 & 1 \\ -489,984 & 1 \end{bmatrix}$$

$$\begin{bmatrix} u \\ v \end{bmatrix} = (H^T H)^{-1} H^T K = \begin{bmatrix} 0.28 \\ 86421.56 \end{bmatrix}$$

**Step 5:** Construct GM (1, 1) prediction equation, Equations (10) and (11). The predicted results are shown in Table 6 as follows.
Table 6. Value of prediction of ECOM01 (Amazon) assets (2016–2022).

| k (Year) | \( X^{(1)}(k) \) | Value | \( X^{(0)}(k) \) | Value |
|----------|------------------|-------|------------------|------|
| k = 0, (2016) | 83,402 | 83,402 |
| k = 1, (2017) | 209,758.64 | 126,356.64 |
| k = 2, (2018) | 376,609.03 | 166,850.40 |
| k = 3, (2019) | 596,930.30 | 220,321.27 |
| k = 4, (2020) | 887,858.36 | 290,928.06 |
| k = 5, (2021) | 1,272,020.71 | 384,162.35 |
| k = 6, (2022) | 1,779,296.32 | 507,275.61 |

Note: calculated by the authors.

Other variables are calculated using the same methodology. All forecast values of input and output variables for the period from 2020 to 2022 are shown in Table A1 (Appendix A).

Step 6: Evaluate the accuracy of the results, Equation (12). The summary of the MAPE of the DMUs is presented in Table 7. From the results, the range of MAPE values is from 0.20% to 3.43%. These values are less than 10%; hence, the forecast results have high accuracy.

Table 7. The summary of mean absolute percentage error (MAPE) of the decision-making units (DMUs).

| Company       | Assets | Liabilities | Equity | Revenue | Gross profit | Average |
|---------------|--------|-------------|--------|---------|--------------|---------|
| Amazon        | 2.14%  | 3.14%       | 2.04%  | 1.28%   | 2.51%        | 2.22%   |
| eBay          | 1.60%  | 0.05%       | 9.85%  | 1.85%   | 2.31%        | 3.13%   |
| Walmart       | 0.70%  | 1.30%       | 0.31%  | 0.03%   | 0.03%        | 0.47%   |
| Target        | 0.27%  | 1.08%       | 1.71%  | 0.23%   | 1.12%        | 0.88%   |
| BestBuy       | 0.81%  | 0.24%       | 3.02%  | 0.84%   | 0.61%        | 1.10%   |
| Groupon       | 0.22%  | 1.16%       | 6.53%  | 1.60%   | 1.62%        | 2.22%   |
| Overstock     | 2.67%  | 0.01%       | 6.23%  | 4.43%   | 3.79%        | 3.43%   |
| Costco        | 0.14%  | 0.32%       | 0.23%  | 0.27%   | 0.04%        | 0.20%   |
| Etsy          | 3.32%  | 7.68%       | 0.07%  | 0.84%   | 1.30%        | 2.64%   |
| Lowe’s        | 0.80%  | 0.03%       | 6.60%  | 0.25%   | 1.05%        | 1.75%   |

Note: calculated by the authors.

4.3. Results of Malmquist-I-C

4.3.1. Pearson Correlation

According to Wang et al. [66], the Pearson coefficient, i.e., the isotropic condition, must be tested before using the DEA Malmquist model. This Pearson coefficient shows the correlation of two factors, where their values range from \((-1; 0; +1)\), presenting the relationship in negative, none, and positive linear relationships, respectively. The DEA model needs data in a positive relationship. Table 8 shows the Pearson correlation indexes for the whole period, including the historical period from 2016 to 2019 and the future period from 2020 to 2022. Pearson correlation matrices coefficients are accompanied by \(p\)-values, which are significant at the 0.01 level (2-tailed). From the results, all coefficients are statistically significant, and the range of Pearson values is from 0.894 to 1. The strongest correlations are between assets and liabilities. Hence, the data is verified for using the Malmquist-I-C model.

4.3.2. Technical Efficiency Change

Technical efficiency assessment in the e-commerce industry is essential as technical development increases competitiveness through product diversification and effective services. The catch-up index is
used to assess annual technical efficiency changes. Thus, e-commerce companies should pay attention
to technical efficiency improvement by observing these indexes periodically.

Table 8. Pearson correlation (2016–2022).

|         | Inputs        | Outputs       | Assets          | Liabilities   | Equity          | Revenue        | Gross profit   |
|---------|---------------|---------------|-----------------|---------------|-----------------|----------------|----------------|
| Pearson correlation | 1             | 0.996 **      | 0.988 **       | 0.908 **      | 0.952 **       |                |                |
| p-value | 0.000         | 0.000         | 0.000           | 0.000         | 0.000           |                |                |
| Sample size | 70           | 70            | 70              | 70            | 70              |                |                |
| Liabilities | Pearson correlation | 0.996 ** | 1               | 0.972 **      | 0.894 **       | 0.940 **       |                |
| p-value | 0.000         | 0.000         | 0.000           | 0.000         | 0.000           |                |                |
| Sample size | 70           | 70            | 70              | 70            | 70              |                |                |
| Equity | Pearson correlation | 0.988 ** | 0.972 **       | 1             | 0.909 **       | 0.952 **       |                |
| p-value | 0.000         | 0.000         | 0.000           | 0.000         | 0.000           |                |                |
| Sample size | 70           | 70            | 70              | 70            | 70              |                |                |
| Revenue | Pearson correlation | 0.908 ** | 0.894 **      | 0.909 **      | 1              | 0.980 **       |                |
| p-value | 0.000         | 0.000         | 0.000           | 0.000         | 0.000           |                |                |
| Sample size | 70           | 70            | 70              | 70            | 70              |                |                |
| Gross profit | Pearson correlation | 0.952 ** | 0.940 **      | 0.952 **      | 0.980 **       | 1              |                |
| p-value | 0.000         | 0.000         | 0.000           | 0.000         | 0.000           |                |                |
| Sample size | 70           | 70            | 70              | 70            | 70              |                |                |

Note: ** denotes correlation is significant at the 0.01 level (2-tailed).

Table A2 (Appendix A) shows the year-over-year catch-up indexes of 10 e-commerce companies
from 2016 to 2019 and the estimated indexes from 2020 to 2022. The catch-up index indicates the
progress (if score >1) or the regress (if score < 1) in the technical efficiency of the DMUs. With the average
year-to-year catch-up indexes of all DMUs at 1.02688 in 2016–2017, 1.04086 in 2017–2018, and 1.00796 in
2018–2019, it can be concluded that most DMUs achieved high technical efficiency during the past four
years (2016–2019). Meanwhile, technical efficiency started to decrease in 2019–2020, being regressive
with a score of 0.97124. From 2020 to 2022, the technical efficiency of the e-commerce industry is
expected to be below 1, having scores of 0.98084 and 0.99023 in 2020–2021 and 2021–2022, respectively.
For the whole research period of 2016–2022, it is remarkable that while only three out of 10 DMUs
achieved average catch-up indexes above 1 (ECOM02-eBay, ECOM05-BestBuy, ECOM10-Lowe’s),
the overall average catch-up index of all DMUs = 1.003 (>1), meaning that there are significant
differences in technical efficiency between the DMUs. While the maximum average index is 1.22383
(ECOM02-eBay), the minimum one is 0.90141 (ECOM09-Etsy), the difference being 0.30242.

During 2016–2017, 4 out of 10 DMUs achieved high technical efficiency, which are
ECOM07-Overstock, ECOM08-Costco, ECOM09-Etsy, and ECOM10-Lowe’s, with scores of 1.10547,
1.09015, 1.60931, and 1.02847, respectively. ECOM01-Amazon had the lowest catch-up index at 0.82308.
Surprisingly, the DMUs that had low technical efficiency in 2016–2017, with scores below 1 (namely,
ECOM01-Amazon, ECOM02-eBay, ECOM03-Walmart, ECOM04-Target, and ECOM05-BestBuy),
had impressive improvements in 2017–2018, with scores greater than 1; ECOM02-eBay became
the most technically efficient e-commerce company during this period, with the score at 1.37101.
In the meantime, highly technically effective companies in 2016–2017 (i.e., ECOM07-Overstock,
ECOM08-Costco, and ECOM09-Etsy) had a sudden decline in their catch-up indexes (below 1) in
2017–2018. Notably, the technical performance of ECOM09-Etsy was tremendously decreased in
2017–2018, having the highest score of 1.60931 in 2016–2017 and declining in 2017–2018 by one
third to only 0.53897, becoming the least-effective company in 2017–2018. The catch-up index of
ECOM10-Lowe’s increased from 1.02847 in 2016–2017 to 1.28029 in 2017–2018. From 2018–2019,
the DMUs began to reduce their technical performance, except for ECOM02-eBay, which saw its
catch-up score increase from 1.37101 in 2017–2018 to 1.41764 in 2018–2019, being the most-effective
company in this period and maintaining the highest position in later periods. This DMU and ECOM05-BestBuy were the only two companies that maintained high technical efficiency during the research period. Meanwhile, ECOM09-Etsy slightly increased their index from 0.53897 in 2017–2018 to 0.82868 in 2018–2019 but remained the most underperforming company during this period and throughout the later periods. In 2019–2020, as discussed, only ECOM02-eBay and ECOM05-BestBuy had catch-up indexes higher than 1; ECOM09-Etsy had the lowest score at 0.85223.

For each DMU, there was not much difference between their past and future technical performances. In the period 2020–2022, ECOM02-eBay and ECOM05-BestBuy are predicted to maintain high technical efficiency, with expected catch-up indexes higher than 1. Meanwhile, the remaining DMUs are predicted to have no improvement in their technical efficiency in the 2020–2022 period, except for ECOM06-Groupon, which scored lower than 1 during 2016–2020 but is expected to increase their index to more than 1 during 2020–2022.

Figure 4 gives a diagram view of DMUs’ catch-up indexes throughout 2016–2022. It is worth looking at the chart of ECOM03-Walmart. Overall, while most DMUs had stable technical efficiency change during the research period, only ECOM03-Walmart had the most fluctuating and lowest technical performance. It had an outstanding catch-up index in 2016–2017, outstripping the remaining DMUs in this period, then dropped tremendously to the worst technical efficiency change index in 2017–2018 by far. Afterward, the value of ECOM03-Walmart’s catch-up index increased and remained stable in later periods, but it is still the lowest among all DMUs.

![Technical Efficiency Chart](image-url)

**Figure 4.** The technical efficiency change (catch-up) of DMUs (2016–2022).

4.3.3. Technological Change

Table A3 (Appendix A) demonstrates the year-over-year frontier-shift indexes of 10 DMUs in the past four years (2016–2020) and the future period of 2020–2022. Frontier-shift indexes express the technological change (efficiency-frontiers) of the DMUs between the two periods. During 2016–2020, most DMUs showed common trends, severely declining from 2016–2017 to 2017–2018, slightly increasing from 2017–2018 to 2018–2019, and then seeing rapid growth from 2018–2019 to 2019–2020. It is remarkable that in 2016–2017, all DMUs obtained frontier-shift indexes higher than 1, indicating that e-commerce companies made efforts to develop and innovate technology and achieved good results during this period. ECOM03-Walmart achieved the highest score of 1.15851, while ECOM10-Lowe’s had the lowest score at 1.02773. The average technological efficiency in this period resulted in a progressive score of 1.06536. Nevertheless, they could not maintain this status in the next period (2017–2018), as most of the frontier-shift indexes declined to lower than 1, except for ECOM06-Groupon and ECOM09-Etsy. That resulted in a regressive score of 0.99688 in this period. After the previous decline, seven out of 10 DMUs showed noticeable improvement in 2018–2019, in which ECOM01-Amazon, ECOM03-Walmart, ECOM05-BestBuy, and ECOM10-Lowe’s achieved high technological efficiency, with scores of 1.01830, 1.01335, 1.00335, and 1.03324, respectively. ECOM09-Etsy suffered a serious decline in technological efficiency, being the most efficient company in 2017–2018, and then becoming...
the worst-performing company in 2018–2019, with a score of 0.94924. Although most frontier-shift indicators increased in 2018–2019, the remaining witnessed dramatic declines; hence, the average score was 0.99144 in this period. In 2019–2020, the companies continued to improve their technological efficiency. ECOM07-Overstock increased its frontier-shift index from 0.95196 in the last period to 0.99817 in 2019–2020, while the remaining DMUs obtained progressive scores (higher than 1) in this period. The most technologically efficient company in this period was ECOM04-Target, with a score of 1.11162; hence, the average score in 2019–2020 increased to 1.06963.

Frontier-shift indexes in 2020–2021 are not likely to change much compared to those of 2019–2020, as ECOM07-Overstock will remain at a regressive score of 0.95373, while the remaining DMUs are expected to maintain their good technological efficiency at scores higher than 1 in this period. ECOM10-Lowe’s is projected to obtain the highest score of 1.11162, and the expected average score of all DMUs is 1.05600. In 2021–2022, over half of all DMUs are anticipated to slightly decrease their frontier-shift indexes, in which ECOM06-Groupon and ECOM08-Costco will have a decline in their scores to lower than 1, at 0.93064 and 0.98965, respectively. ECOM07-Overstock is predicted to show no improvement in 2021–2022, with a score of 0.95037. ECOM09-Etsy is predicted to have the highest score at 1.19543, and the average score of all DMUs will slightly increase to 1.05971 in 2021–2022. Over the whole research period (2016–2022), a vast majority of DMUs (ECOM01-Amazon, ECOM02-eBay, ECOM03-Walmart, ECOM04-Target, ECOM05-BestBuy, ECOM06-Groupon, ECOM09-Etsy, and ECOM10-Lowe’s) will achieve high technological efficiency as the overall average frontier-shift score of all DMUs is 1.03984.

As discussed in the section on technical change, ECOM03-Walmart had the least-stable and lowest technical efficiency performance in 2017–2018. However, this DMU had an outstanding frontier-shift index in 2017–2018, outperforming the other DMUs in the technology development in that year, although it has a fluctuating frontier-shift index throughout 2016–2022, as shown in Figure 5. The technological change of ECOM03-Walmart suffered a dramatic decline in 2018–2019 but then kept rising, and it is expected to be the most technologically efficient company in 2021–2022.

![Technological Efficiency](image)

**Figure 5.** The technological change (frontier) of DMUs (2016–2022).

### 4.3.4. Malmquist Productivity Index (MPI)

MPI is applied to evaluate the performance of global e-commerce companies as it measures the change in total factor productivity of the DMUs in terms of technical efficiency (through the catch-up index) and technological change (through the frontier-shift index). Table A4 (Appendix A) shows the year-over-year MPI of 10 e-commerce companies from 2016 to 2019 and the estimated indexes from 2020 to 2022, while Figure 6 provides a diagram view. It is worth noting that the MPI line charts of the DMUs in Figure 6 have the same trends as their charts of the catch-up index in Figure 4. An explanation
for these patterns will be discussed in the next section. Overall, the MPIs of most DMUs tended to decrease from 2016–2017 to 2017–2018, continuing to fall from 2017–2018 to 2018–2019, and then gradually rising in 2019–2020. Not many DMUs are likely to have an improvement in their total factor productivity in 2020–2021. Moreover, the MPIs are predicted to stay unchanged in 2021–2022 compared to 2020–2021. On average, only ECOM02-eBay, ECOM05-BestBuy, and ECOM10-Lowe’s have achieved the most stable and best performances in terms of technical and technological efficiency during the total research period (2016–2022) as their MPIs are recorded as being higher than 1 for almost all periods. Their average MPI for the whole research period is 1.26852, 1.13751, and 1.12290, respectively. However, the overall average MPI of all DMUs during 2016–2022 is 1.03940, indicating that the difference in total factor productivity between DMUs is relatively significant. While the maximum average MPI is 1.26852 (ECOM02-eBay), the minimum one is 0.96486 (ECOM06-Groupon), the difference being 0.30366.

Figure 6. The Malmquist productivity index of DMUs (2016–2022).

In 2016–2017, seven out of 10 DMUs, namely, ECOM03-Walmart, ECOM04-Target, ECOM05-BestBuy, ECOM07-Overstock, ECOM08-Costco, ECOM09-Etsy, and ECOM10-Lowe’s, achieved progress in total factor productivity. ECOM09-Etsy had an impressive score of 1.78641, while ECOM01-Amazon only obtained 0.87535 as its productivity score. The average MPI of all DMUs in this period is 1.09508.

In 2017–2018, ECOM01-Amazon, ECOM02-eBay, ECOM05-BestBuy, and ECOM10-Lowe’s showed considerable improvement in their productivity while the others started to decline. Notably, ECOM09-Etsy suffered a steep decline in its MPI, falling sharply from 1.78641 in 2016–2017 to only 0.65979 in 2017–2018, being the least-efficient company, while the other rivals were above 0.85 in this period. Overall, half of the DMUs achieved progressive MPIs, namely, ECOM01-Amazon, ECOM02-eBay, ECOM04-Target, ECOM05-BestBuy, and ECOM10-Lowe’s, with scores of 1.06257, 1.30645, 1.01723, 1.23866, and 1.17862, respectively. The average MPI of all DMUs in this period was 1.02223.

During 2018–2019, most DMUs performed inefficiently, with MPIs less than 1; only three DMUs (ECOM02-eBay, ECOM05-BestBuy, and ECOM10-Lowe’s) achieved progress in total factor productivity, with scores of 1.39286, 1.06717, and 1.28749, respectively. ECOM09-Etsy had a slight improvement in its MPI to 0.78661 but was still the lowest score in this period. The average MPI of all DMUs in 2018–2019 was down to 1.00075.

ECOM02-eBay, ECOM05-BestBuy, and ECOM10-Lowe’s still maintained their progress in total factor productivity in 2019–2020 with MPIs of 1.25011, 1.23382, and 1.03267, respectively. ECOM01-Amazon is the only one among the remaining DMUs to have an improvement in total
productivity index, increasing to 1.01916 in this period. ECOM09-Etsy had the lowest MPI of 0.92157. However, the average MPI of all DMUs saw a slight increase to 1.03626 in this period.

For 2020–2022, ECOM01-Amazon, ECOM02-eBay, ECOM05-BestBuy, and ECOM10-Lowe’s are likely to maintain their good performance as their expected MPIs are higher than 1. In detail, ECOM01-Amazon, ECOM02-eBay, ECOM05-BestBuy, and ECOM10-Lowe’s are predicted to score 1.00187, 1.34894, 1.14872, and 1.08416 in 2020–2021 and 1.00890, 1.39524, 1.12752, and 1.09750 in 2021–2022, respectively. After an inefficient period in terms of both technical and technological efficiency in 2016–2020, ECOM06-Groupon is suddenly expected to achieve progressive MPIs of 1.03121 in 2020–2021 and 1.06823 in 2021–2022. On the other hand, ECOM09-Etsy is not likely to catch up with the other rivals and is predicted to be the worst-performing e-commerce company with MPIs of 0.88807 in 2020–2021 and 0.91141 in 2021–2022. Frontier-shift indexes in 2020–2021 are not likely to change much compared to those of 2019–2020, as ECOM07-Overstock will continue to have a regressive MPI of 0.95373, while the remaining DMUs are expected to maintain their good technological efficiency with scores higher than 1 in this period. ECOM10-Lowe’s is projected to obtain the highest score of 1.10637, and the expected average score of all DMUs is 1.05600. In 2021–2022, over a half of all DMUs are anticipated to slightly decrease their frontier-shift indexes, in which ECOM06-Groupon and ECOM08-Costco will have a decline in their scores to lower than 1, at 0.93064 and 0.98965, respectively. ECOM07-Overstock is predicted to show no improvement in 2021–2022, with a score of 0.95037. ECOM09-Etsy is predicted to have the highest score at 1.19543, and the average score of all DMUs will slightly increase to 1.05971 in 2021–2022. Over the whole research period (2016–2022), a vast majority of DMUs (ECOM01-Amazon, ECOM02-eBay, ECOM03-Walmart, ECOM04-Target, ECOM05-BestBuy, ECOM06-Groupon, ECOM09-Etsy, and ECOM10-Lowe’s) will have achieved high technological efficiency as the overall average frontier-shift score of all DMUs is 1.03984.

As discussed in the section on technical change, ECOM03-Walmart had the least-stable and lowest technical efficiency performance in 2017–2018. However, this DMU had an outstanding frontier-shift index in 2017–2018, outperformed the other DMUs in technology development in this year, although it has a fluctuating frontier-shift index throughout 2016–2022, as shown in Figure 5. The technological change of ECOM03-Walmart suffered a dramatic decline in 2018–2019, but then kept rising, and it is expected to be the most technologically efficient company in 2021–2022.

4.3.5. The Relationship among Technical, Technological, and MPI Change

Figure 7 demonstrates the relationship between the average technical efficiency and technological change indexes and MPIs of the DMUs. As most e-commerce companies have progressed in technological development during the studied period, with 8 out of 10 DMUs achieving average frontier-shift indexes greater than 1, the chart of technological change indexes between the DMUs shows a stable line. In the meantime, fluctuating lines are demonstrated in the charts of technical efficiency and the Malmquist productivity index (MPI). This is because there are significant differences between the average technical efficiency change indexes of the DMUs. Additionally, since the MPI is the product of the catch-up index (technical change) and frontier-shift index (technological change), then the pattern of the MPI chart should be almost the same as the technical change’s line chart, as can be seen in Figure 7. Hence, the productivity growth of each DMU is nearly decided by its technical efficiency change. That also explains why trends of MPIs in Figure 6 are the same as those of catch-up indexes for all DMUs, as in Figure 4. As e-commerce leaders realize how technology innovation has become the main fuel behind evolution and success in the e-commerce world, they are focusing more on this area. Hence, e-commerce companies’ technological growth is nearly the same for this period. However, to win the race of e-commerce, companies should make better efforts to enhance technical production and efficiency and to maximize their resources, such as labor, material and equipment supplies, and capital.
5. Discussions and Conclusions

By conducting performance prediction and evaluation of the e-commerce industry, the integrated model is proposed to obtain the technical efficiency change, technological change, and total productivity factor change index for the top 10 e-commerce companies in the US market, which are Amazon, eBay, Walmart, Target, BestBuy, Groupon, Overstock, Costco, Etsy, and Lowe’s for 2016–2022. In this model, the inputs are assets, liabilities, and equity, while revenue and gross profit are considered outputs. The results show that as all companies performed equally well in developing technology as most of their frontier-shift indexes achieved progressive scores of higher than 1. Meanwhile, their technical efficiency indexes are significantly different from each other. Therefore, as a product of technical and technological performance, their MPIs depend mostly on their technical change indexes.

In terms of technical progress, on average, eBay, BestBuy, and Lowe’s are the only three DMUs to have a high technical performance for 2016–2022, of which eBay and BestBuy are the best-performing and most stable e-commerce marketplaces, with catch-up indexes higher than 1 for most research periods. They are followed by Lowe’s, with high technical performance in 2016–2019 that gradually waned; it is predicted to remain regressive during 2020–2022. The remaining e-commerce companies (7 out of 10 DMUs) need more improvement in this aspect, especially Etsy, which had the lowest average catch-up index. It is worth noting that most DMUs performed equally well in technology development, with 8 out of 10 obtaining high frontier-shift indexes on average. Although performing worst in the technical aspect, Etsy progressed in technology and innovation, becoming the best-performing company regarding technological efficiency. In the meantime, Overstock and Costco are the only two DMUs to have regressed in this aspect. As total factor productivity is the product of technical and technological efficiency, in order to achieve a progressive outcome, e-commerce companies need to balance both technical and technological performance. Based on the results, having the highest technical change indexes, eBay, BestBuy, and Lowe’s once again are the only three DMUs to achieve MPIs higher than 1 on average. This also implies that these DMUs are the best and most stable companies in the e-commerce industry for the studied period. Moreover, Walmart, the world’s largest brick-and-mortar retailer, has been pushing the envelope to become a tech-centric company rather than a conventional retailer, as it is one of the top ten largest e-commerce retailers in the US in 2020 [75]. It is worth looking at this company’s figures and charts since it has contradictory development in technical and technological efficiency performance, with the most differentiated figures compared to those of the remaining companies (shown in Figures 4–6). This company progressed in technology during the studied period, with outstanding performance in 2017–2018 but also the worst technical efficiency change in this period by far. This is because it had shifted its focus and strategies to become a high-tech innovator in e-commerce [76].

The contributions of the paper are three-fold. (1) The paper proposes an evaluation method of the e-commerce industry that combines the Grey prediction model GM (1, 1) and the Malmquist-I-C
model. From our literature review, this hybrid approach is introduced for the first time in our study to predict and evaluate the past, current, and future performances of e-commerce businesses. (2) The empirical results of this paper provide comprehensive and practical insights into the top 10 US e-commerce companies’ performance in recent years. As a matter of fact, instead of being a cause for concern, Covid-19 appears to be a catalyst to exemplify the effectiveness of an e-commerce marketplace in executing its business activities more sustainably [23] and achieving breakthroughs in technology innovation for success in this industry. (3) The authors expect that the results will reflect the current situation of the global e-commerce industry, especially in terms of technological change, through the performance of some successful e-commerce companies. Therefore, managers, policymakers, and investors, not only in the US but in any firm around the world, should consider this paper as a guideline for sustainable development and effective investment decisions in e-commerce.

However, this study has some limitations. First, more companies should have been included to give a more detailed overall view; this is due to the lack of annual reports. Second, this research only considers some specific input and output variables; the use of other ones may lead to different results or enhance the resolution of the empirical results. Moreover, future studies should consider the problem under uncertainty, i.e., stochastic DEA, in order to provide more robust results.

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Appendix A

| DMUs | Company | Assets   | Liabilities | Equity    | Revenue   | Gross Profit |
|------|---------|----------|-------------|-----------|-----------|--------------|
| Year of 2020 |
| ECOM01 | Amazon | 290,928  | 202,011     | 89,816    | 350,769   | 99,956       |
| ECOM02 | eBay   | 15,629   | 14,130      | 2307      | 11,639    | 8969         |
| ECOM03 | Walmart | 228,980  | 150,349     | 79,436    | 529,381   | 131,438      |
| ECOM04 | Target | 43,263   | 31,655      | 11,662    | 78,309    | 23,034       |
| ECOM05 | BestBuy | 12,333   | 9848        | 2630      | 45,040    | 10,288       |
| ECOM06 | Groupon | 1547     | 1072        | 501       | 2008      | 1141         |
| ECOM07 | Overstock | 422     | 230         | 192       | 1420      | 286          |
| ECOM08 | Costco | 50,718   | 32,440      | 18,405    | 166,322   | 21,293       |
| ECOM09 | Etsy   | 2352     | 2129        | 411       | 1096      | 739          |
| ECOM10 | Lowe’s | 34,835   | 32,422      | 3169      | 74,823    | 23,370       |
| Year of 2021 |
| ECOM01 | Amazon | 384,162  | 256,636     | 132,066   | 437,374   | 133,119      |
| ECOM02 | eBay   | 13,153   | 13,059      | 1508      | 12,338    | 9503         |
| ECOM03 | Walmart | 240,639  | 163,707     | 78,993    | 544,694   | 133,782      |
| ECOM04 | Target | 45,450   | 33,735      | 11,837    | 81,559    | 23,804       |
| ECOM05 | BestBuy | 11,894   | 10,086      | 2182      | 46,951    | 10,564       |
| ECOM06 | Groupon | 1505     | 978         | 610       | 1781      | 1078         |
| ECOM07 | Overstock | 415     | 220         | 195       | 1309      | 267          |
| ECOM08 | Costco | 56,655   | 35,217      | 21,826    | 180,845   | 22,893       |
| ECOM09 | Etsy   | 3797     | 4680        | 416       | 1488      | 1005         |
| ECOM10 | Lowe’s | 34,885   | 34,054      | 2473      | 78,340    | 23,595       |
Table A1. Cont.

| DMUs   | Company   | Assets      | Liabilities  | Equity    | Revenue    | Gross Profit |
|--------|-----------|-------------|--------------|-----------|------------|--------------|
|        |           | Year of 2022 |              |           |            |              |
| ECOM01 | Amazon    | 507,276     | 326,032      | 194,193   | 545,361    | 177,285      |
| ECOM02 | eBay      | 11,069      | 12,068       | 986       | 13,080     | 10,069       |
| ECOM03 | Walmart   | 252,893     | 178,251      | 78,553    | 560,449    | 136,168      |
| ECOM04 | Target    | 47,747      | 35,952       | 12,015    | 84,943     | 24,599       |
| ECOM05 | BestBuy   | 11,470      | 10,328       | 1810      | 48,944     | 10,849       |
| ECOM06 | Groupon   | 1,464       | 893          | 742       | 1579       | 1019         |
| ECOM07 | Overstock | 407         | 210          | 198       | 1,206      | 249          |
| ECOM08 | Costco    | 63,288      | 38,232       | 25,883    | 196,636    | 24,613       |
| ECOM09 | Etsy      | 6129        | 10,289       | 421       | 1,366      | 23,822       |
| ECOM10 | Lowe’s    | 34,935      | 35,768       | 1930      | 80,232     | 23,666       |

Note: calculated by the authors.

Table A2. The technical efficiency change (catch-up) of DMUs.

| DMUs   | Company   | 2016 to 2017 | 2017 to 2018 | 2018 to 2019 | 2019 to 2020 | 2020 to 2021 | 2021 to 2022 | Avg     | Max     | Min     | SD      |
|--------|-----------|--------------|--------------|--------------|--------------|--------------|--------------|---------|---------|---------|---------|
| ECOM01 | Amazon    | 0.82308      | 1.06941      | 0.88021      | 0.92066      | 0.93456      | 0.95065      | 0.92976  |         |         |         |
| ECOM02 | eBay      | 0.88882      | 1.37101      | 1.41764      | 1.20585      | 1.23150      | 1.22383      |         |         |         |         |
| ECOM03 | Walmart   | 0.89368      | 1.01554      | 0.93201      | 0.88907      | 0.90135      | 0.90316      | 0.92247  |         |         |         |
| ECOM04 | Target    | 0.97516      | 1.04439      | 0.96400      | 0.89821      | 0.91237      | 0.91609      | 0.95170  |         |         |         |
| ECOM05 | BestBuy   | 0.90731      | 1.28599      | 1.06360      | 1.18930      | 1.07923      | 1.03961      | 1.09417  |         |         |         |
| ECOM06 | Groupon   | 0.94735      | 0.85303      | 0.87875      | 0.88941      | 1.00751      | 1.14784      | 0.95398  |         |         |         |
| ECOM07 | Overstock | 1.10547      | 0.98068      | 0.89715      | 0.98274      | 0.98197      | 0.98194      | 0.98907  |         |         |         |
| ECOM08 | Costco    | 1.09015      | 0.96925      | 0.97150      | 0.92971      | 0.96310      | 0.98053      | 0.98404  |         |         |         |
| ECOM09 | Etsy      | 1.60931      | 0.53897      | 0.82868      | 0.85223      | 0.81684      | 0.76241      | 0.90141  |         |         |         |
| ECOM10 | Lowe’s    | 1.02847      | 1.28029      | 1.24607      | 0.95076      | 0.97993      | 0.99184      | 1.07956  |         |         |         |

Avg: 1.02688, Max: 1.60931, Min: 0.82308, SD: 0.22387

Note: calculated by the authors.

Table A3. The technological change (frontier) of DMUs.

| DMUs   | Company   | 2016 to 2017 | 2017 to 2018 | 2018 to 2019 | 2019 to 2020 | 2020 to 2021 | 2021 to 2022 | Avg     | Max     | Min     | SD      |
|--------|-----------|--------------|--------------|--------------|--------------|--------------|--------------|---------|---------|---------|---------|
| ECOM01 | Amazon    | 1.06351      | 0.99361      | 1.01830      | 1.10700      | 1.07202      | 1.06127      | 1.05262  |         |         |         |
| ECOM02 | eBay      | 1.03232      | 0.95291      | 0.98252      | 1.03671      | 1.09536      | 1.13601      | 1.03931  |         |         |         |
| ECOM03 | Walmart   | 1.15851      | 0.97560      | 1.01755      | 1.09429      | 1.07026      | 1.06654      | 1.06379  |         |         |         |
| ECOM04 | Target    | 1.05307      | 0.97399      | 0.99794      | 1.11162      | 1.08182      | 1.07611      | 1.04909  |         |         |         |
| ECOM05 | BestBuy   | 1.11222      | 0.96319      | 1.00335      | 1.03744      | 1.06439      | 1.08456      | 1.04419  |         |         |         |
| ECOM06 | Groupon   | 1.03612      | 1.04945      | 0.99005      | 1.10286      | 1.02353      | 0.93064      | 1.01469  |         |         |         |
| ECOM07 | Overstock | 1.03057      | 0.99590      | 0.95196      | 0.99817      | 0.95373      | 0.95037      | 0.98012  |         |         |         |
| ECOM08 | Costco    | 1.02949      | 0.96392      | 0.97021      | 1.04068      | 1.00535      | 0.98965      | 0.99988  |         |         |         |
| ECOM09 | Etsy      | 1.11005      | 1.22418      | 0.94924      | 1.08137      | 1.08720      | 1.19543      | 1.10791  |         |         |         |
| ECOM10 | Lowe’s    | 1.02773      | 0.92059      | 1.03324      | 1.08615      | 1.10617      | 1.10652      | 1.04677  |         |         |         |

Avg: 1.06536, Max: 1.15851, Min: 1.02773, SD: 0.04581

Note: calculated by the authors.
Table A4. The Malmquist productivity index of DMUs.

| DMUs   | Company | 2016 to 2017  | 2017 to 2018  | 2018 to 2019  | 2019 to 2020  | 2020 to 2021  | 2021 to 2022  | Avg     |
|--------|---------|---------------|---------------|---------------|---------------|---------------|---------------|---------|
| ECOM01 | Amazon  | 0.87535       | 1.06257       | 0.89631       | 1.01916       | 1.00187       | 1.00890       | 0.97736 |
| ECOM02 | eBay    | 0.91755       | 1.30645       | 0.94837       | 0.97290       | 0.96468       | 0.96326       | 0.97922 |
| ECOM03 | Walmart | 1.03534       | 0.99076       | 0.94837       | 0.97290       | 0.96468       | 0.96326       | 0.97922 |
| ECOM04 | Target  | 1.02691       | 1.01723       | 0.96202       | 0.99846       | 0.98702       | 0.98581       | 0.99624 |
| ECOM05 | BestBuy | 1.00914       | 1.23866       | 1.06717       | 1.23382       | 1.14872       | 1.12752       | 1.13751 |
| ECOM06 | Groupon | 0.98157       | 0.85726       | 0.87000       | 0.98089       | 0.96825       | 0.96486       | 0.96486 |
| ECOM07 | Overstock| 1.13928       | 0.97666       | 0.85406       | 0.98543       | 0.93654       | 0.93320       | 0.97086 |
| ECOM08 | Costco  | 1.12229       | 0.93429       | 0.94256       | 0.96753       | 0.96825       | 0.97038       | 0.98422 |
| ECOM09 | Etsy    | 1.78641       | 0.65979       | 0.78661       | 0.92157       | 0.88807       | 0.91141       | 0.99231 |
| ECOM10 | Lowe’s  | 1.05699       | 1.17862       | 1.28749       | 1.03267       | 1.08416       | 1.09750       | 1.12290 |

Avg 1.09508 1.02223 1.00075 1.03626 1.03595 1.04615 1.03940
Max 1.78641 1.30645 1.06717 1.23382 1.14872 1.12752 1.13751
Min 0.87535 0.65979 0.78661 0.92157 0.88807 0.91141 0.96486
SD 0.25612 0.18948 0.19533 0.11256 0.13250 0.14149 0.10217

Note: calculated by the authors.

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