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Malmquist Productivity Analysis of Top Global Automobile Manufacturers

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Abstract: The automobile industry is one of the largest economies in the world, by revenue. Being one of the industries with higher employment output, this has become a major determinant of economic growth. In view of the declining automobile production after a period of continuous growth in the 2008 global auto crisis, the re-evaluation of automobile manufacturing is necessary. This study applies the Malmquist productivity index (MPI), one of the many models in the Data Envelopment Analysis (DEA), to analyze the performance of the world's top 20 automakers over the period of 2015–2018. The researchers assessed the technical efficiency, technological progress, and the total factor productivity of global automobile manufacturers, using a variety of input and output variables which are considered to be essential financial indicators, such as total assets, shareholder's equity, cost of revenue, operating expenses, revenue, and net income. The results show that the most productive automaker on average is Volkswagen, followed by Honda, BAIC, General Motors, and Suzuki. On the contrary, Mitsubishi and Tata Motors were the worst-performing automakers during the studied period. This study provides a general overview of the global automobile industry. This paper can be a valuable reference for car managers, policymakers, and investors, to aid their decision-making on automobile management, investment, and development. This research is also a contribution to organizational performance measurement, using the DEA Malmquist model.

Keywords: data envelopment analysis (DEA); Malmquist productivity index (MPI); catch-up efficiency; frontier-shift; productivity index; technological change; total factor productivity

1. Introduction

It is known that the automobile industry is one of the largest industries and has wide-spread multiple-range products globally. However, despite an evident worldwide growth trend during the 1990s, certain aspects of automotive manufacturing are considered to be more regional, as observed specifically in many developing countries, where vehicle production expanded rapidly during this period. Moreover, at this time, many leading automotive manufacturers have extended some of their operations to these developing countries, driven by the growth in global sales. This move by global producers meant to establish cheaper production sites intended for the manufacturing of selected vehicles and components, and to be able to access new markets for high-end-type vehicles [1].

Some examples of the biggest key players in this industry include the German-based manufacturers Volkswagen and Daimler AG. Japan also has big automotive companies, namely Toyota, Nissan, and Honda. China would not want to be left behind with their very own Shanghai Automotive Industry Corporation (SAIC) Motor and Dongfeng Motor Corporation. Hyundai is a well-known automotive company in Korea, while the United States has a rivalry between Ford and General Motors (GM).

The automotive industry plays a vital role in creating jobs or employment opportunities. With this aspect, the automotive industry scores five in the employment multiplier, while the other industries only got three. In the United States, OEMs (original equipment manufacturers) that make original parts used by automakers directly employ 1.7 million people. They indirectly created 1.5 million jobs, while suppliers and distributors supported an additional 4.8 million jobs. According to the International Organization of Automobile Manufacturers (OICA), each $1 million increase in revenue will create approximately 10 jobs. For industries such as energy and utilities, the ratio is even higher. On a global scale, Volkswagen was the company with the greatest number of employees in the automotive industry in 2015, with more than 570,000 employees. Its rival, Toyota, has 340,000 employees, while another manufacturer, Daimler, has more than 270,000 employees. The large number of people employed by the industry has made it a major determinant of economic growth, as well as recession. The automobile industry is also one of many industries which have tremendous expenses in terms of advertising. For example, during the first half of 2014, GM paid $928 million, and its global-advertising spending reached $5.5 billion in 2013, accounting for 3.54% of its revenue. In that same year, Ford Motors had revenues of USD 139.37 billion and expenditures of USD 4.4 billion. Moreover, Fiat Chrysler Automobiles N.V. (a Dutch-based automaker) has recorded a spending of $2.76 billion, accounting for 3.82% of its revenue. The car-manufacturing business model and value chain are very complex, and car development may take several years. Automakers have been challenged to increase the speed, intelligent design, and efficiency of their vehicles. As a result, many manufacturers focus on innovation. Few people know that, in terms of research and innovation, the world's third largest industry is the automotive-manufacturing industry. In 2013, $100 billion was spent globally, including $18 billion in the United States. For Toyota, investing a lot of money in research helped maintain competition, and in 2013, it spent $8.1 billion on research and development. GM also spent $7.2 billion on research and development that year. It can be considered that this is a very important and influential industry in the global economy [2].

Nowadays, cars and other vehicles have become an integral part of modern society, it streamlines transportation and quickens the pace of society's evolution. The automotive industry looks toward a future of producing more fuel-efficient vehicles to comply with governments' initiative of changing fuel economy standards and the need to reduce dependence on fossil fuels. Therefore, the next generation of automobile industry requires more fuel-efficient engines, advanced and creative design, shared intelligence, and systems engineering. Cars are being improved and developed to use electricity, connected and offering onboard GPS and Wi-Fi capabilities. Some auto manufacturers are even experimenting with self-driving cars. This trend leads to a fierce technological race between all the manufacturers in the automotive industry. The performance of automobile manufacturers must be determined, especially in terms of technical efficiency. The application of the Data Envelopment Analysis Malmquist model in this research will be able to calculate the technical efficiency, as well as the frontier-shift (technological change) of the automobile manufacturers, thereby reflecting their trend of technology development. For these measurements, the authors chose this model to evaluate the performance of 20 global automakers that have a great influence on the global automotive industry during the period of 2015–2018. This will also assist them to better understand the industry as one of the most important and influential industries to the global economy, especially in the context of the risks of a second crisis and in the industry 4.0 race. The authors expect that the research results will reflect an overall picture of the global automotive industry (especially the situation of technical efficiency) through the performance of automotive manufacturers so that automaker managers, policy makers, or investors can use this paper as a basis in drafting automobile management policies, direction for development, and investment decisions. The authors hope that this study will be a valuable reference for the studies of global automotive industry, as well as research on the DEA Malmquist model.

This paper includes five sections. The first section gives an overview about the research background, motivation, purpose, objects, and scope. The second section indicates some previous studies related to performance evaluation, applying data envelopment analysis, especially those that use the Malmquist model. Research procedures and discussions regarding the theory of the Malmquist index model, as well as the Pearson correlation coefficient, are presented in the third section. The fourth section presents the data and calculation, analysis, and evaluation. The last section of this research discusses the conclusion contributions, shortcomings of research, and indicates some direction for the next research.

2. Literature Review

In 1978, Charnes et al. [3] developed Data Envelopment Analysis (DEA). During that time, DEA was a new data-oriented method for the evaluation of Decision-Making Units (DMUs). DMUs is a set of peer entities in which technical efficiencies are calculated. It is a method of optimization with the use of linear programming that will assess the productivity and efficiency of DMUs related to the proportional change in inputs or outputs. The CCR is the first DEA model and is an acronym for Charnes, Cooper, and Rhodes. Then, later, several models of DEA were introduced and broadly applied for performance analysis in many areas, like transportation, mining, logistics, banking, and many other industries and organizations since then. DEA was also used by Martín and Roman [4] in 2001, wherein the performance and technical efficiencies of each individual airports in Spain are analyzed. The results were used to set forth some considerations to the policies that prepare the Spanish airport for the privatization process in 2001. Kulshreshtha et al. [5] utilized DEA to study the productivity of the coal industry of India during the period of 1985–1997 and found that the underground mining has less efficiency than the opencast mining. Leachman [6] used DEA for the development of a quality and output-based performance metric to assess the competitiveness of car firm's manufacturing against its competitors. Pilyavsky et al. [7] deployed DEA to analyze the change in efficiency of 193 community hospitals and polyclinics across the Ukraine, in the 1997–2001 period, and found that the polyclinics somewhat less efficient than community hospitals. Wang et al. [8], in their study, used DEA for the measurement of the marketing and production efficiencies of some 23 companies involved in the Printing Circuit Board (PCB) industry and found that 15 firms need to improve their efficiencies in both production and marketing aspects. Four companies prioritized the progress in their production efficiency, and the remaining four companies focused on enhancing marketing efficiency. Chandraprakaikul and Suebpongsakorn [9], by deploying DEA, found out the weaknesses of 55 logistic firms in Thailand. The goal of their study was to improve the logistics efficiency and evaluate each firm's performances from 2007 to 2010. An application of a DEA with two-stage method was used by Yuan and Tian [10], to analyze the efficiency of resources related to science and technology aspects of several industrial enterprises, along with other factors influencing their performance. Findings show that the elements of the input and output variables are independent. Chang et al. [11] analyzed the environmental efficiency of the transportation sector in China, by using the DEA model to find out the very inefficient environment of the industry. Ren, et al. [12] applied DEA for the assessment of six Chinese biofuel firms' energy efficiency in relation to their life cycle, to determine wasteful energy losses in biofuel production, and indicated that DEA is a feasible and unique tool for establishing efficient scenarios in production of bioethanol. The research also suggested that the most energy-efficient form of ethanol production for China may come from sweet potatoes. DEA has been acknowledged as a practical decision support tool and a valuable analytical research instrument. From a series of the previous studies mentioned above, it is understood that the DEA method has been broadly applied to assess the performance of many companies in different industries, including the automotive industry. These prove that DEA is an effective tool for the authors to evaluate the performance of global automobile manufacturers.

Malmquist productivity index (MPI) is a very useful approach for productivity measurement in DEA. In 1982, Caves introduced MPI and named it after Professor Malmquist (1953), whom the ideas are based upon. The Malmquist productivity index has the components which are used in performance measurement that includes the technical efficiency in technological change and the total factor productivity [13].

As stated in a study by Fuentes and Bañuls, [14] the split of the MPI's Total Productivity Efficiency into two different components, the technical efficiency and the technological, change helps clarify the role of manager or skill level in the final performance data. The DEA Malmquist model has been a very effective method in measuring changes in DMU productivity over the past decade. For example, Färe, et al. [15] used it to analyze productivity growth in developed countries and found that productivity growth in the United States was slightly above average, due to technological changes. The growth in productivity of Japan turned out to be the highest among the samples, and because of the changes in efficiency, Japan's productivity growth is almost half. Fulginiti and Perrin [16] used Malmquist to determine whether the results using this approach can confirm the recorded decline in agricultural productivity from less-developed countries (LDCs) using other methods. The earlier results were confirmed, and we found out that agricultural tax gets the most declining rates in terms of productivity change. Odeck [17] focused on the Norwegian Motor Vehicle Inspection Agencies and measured their efficiency and productivity growth for the period of 1989–1991. Using the Malmquist index, the productivity was described through calculation by DEA, being the ratio between efficiency for the similar production unit in two particular periods. The remarkably positive effect of the frontier technology is observed to be the main contributor to the total productivity growth. The efficiency measures that were calculated show that there are unstable efficiency scores for every unit examined throughout the observed year periods. The size of the units does not have an effects on the efficiency scores. Chen [18] used a non-radial Malmquist productivity index for the change in productivity calculation of three major industries in China: chemicals, textiles, and metallurgical within the four five-year plan periods. The research showed that the economic development plans can be used for the evaluation of productivity and technology changes, using the MPI. Sharma [19] examined the productivity performance of the Indian automobile industry via Total Factor Productivity (TFP) measurement from 1990–1991 to 2003–2004 and explored further the factors influencing the car industry efficiency in India. DEA was also used by Liu and Wang [20] to calculate the three components of Malmquist productivity of some Taiwanese semiconductor packaging and testing firms during the period of 2000 to 2003. Aside from revealing the productivity change patterns and introducing another way to interpret the components of MPI with respect to management aspects, this approach likewise determines any strategic shift of each firm due to isoquant changes. Mazumdar [21] applied MPI to examine the technological gap ratio (TGR), technical efficiency, and change in productivity of pharmaceutical companies among particular sectors in India. The study implies that vertically integrated companies that produce both formulation and bulk drugs exhibit higher efficiency and technological innovation, and it also found that imported technology or the establishment of capital-intensive techniques propels the technological growth of firms.

Wang et al. [22] compared the results of Malmquist productivity index to the Grey Relational Analysis, to assess the intellectual capital management of the pharmaceutical industry in Taiwan. With the combination of these analysis tools, they were able to conclude that, among the 12 pharmaceutical companies, seven of them have efficiently improved their intellectual capital management, while five companies failed during the four-year period of 2005 to 2008. Chang et al. [23] used the Malmquist DEA model to study the productivity changes of accounting firms in the US, right before and after the implementation of the Sarbanes–Oxley Act. The findings indicated that accounting firms exhibited significant growth in productivity efficiency after the actualization of SOX, and these results were better than pre-SOX performances.

These studies cited above prove that the Malmquist productivity index (MPI), which is a DEA-based model, is a very useful tool for measuring the productivity changes of countries, industries, or organizations, through a specific assessment of technical and technological aspects, as well as total factor productivity. Regarding this research, the authors know that car production is a complex activity that combines technical aspects and technological capabilities; therefore, evaluating the performance of an automobile manufacturer not only needs to include an evaluation of overall performance, but it also needs to have specific technical and technological assessments. This Malmquist model is an appropriate research method to perform the most detailed evaluation of the technical, as well as the technological, performance of global automakers. For this reason, the authors chose to apply this Malmquist model to carry out this research.

3. Materials and Methods

3.1. Research Process

In this research, the authors deployed the Malmquist productivity index model in the DEA method, to evaluate the performance of the world's top 20 automakers from 2015 to 2018. The study includes four parts of processes, as shown in Figure 1.

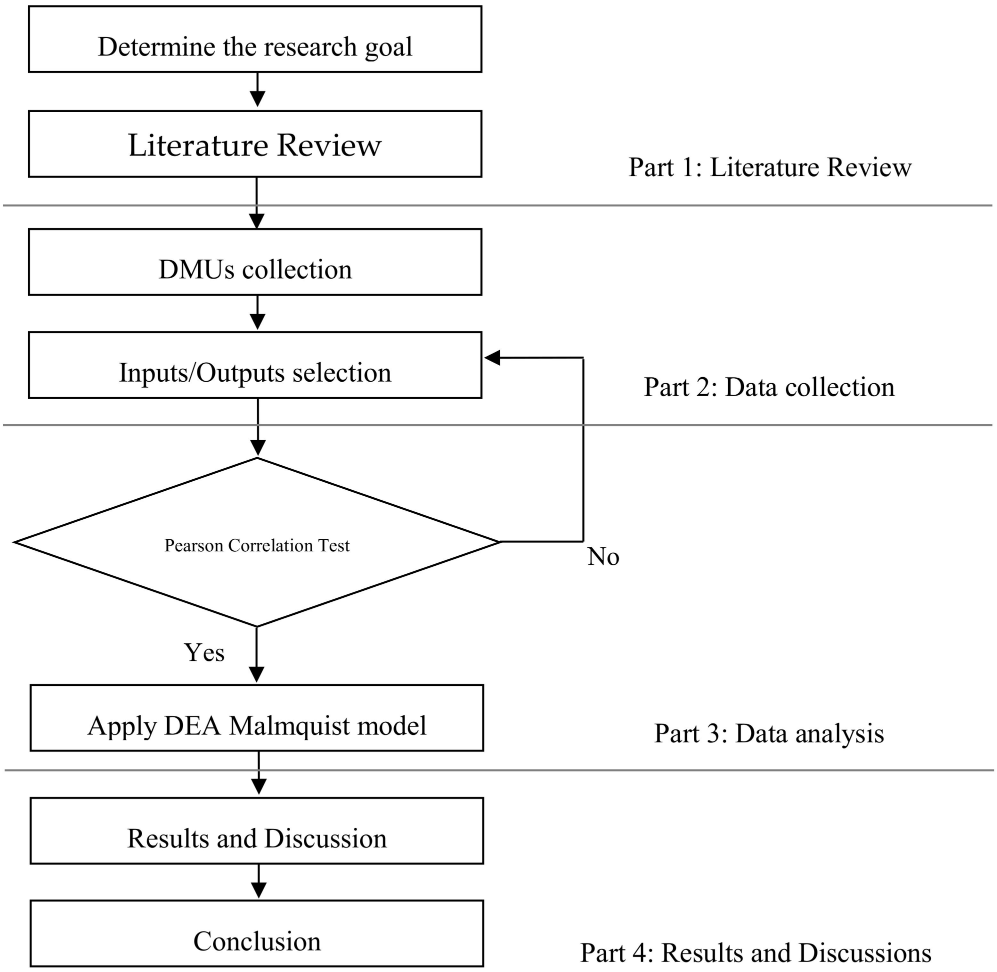

Figure 1. Procedures of research.

Part 1. Literature review: The authors identified the research topic and method, and then learned about the history of studies, using the selected method and the research that is related to the topic, in order to have a research base for conducting this research.

Part 2. Data collection: In this part, the authors selected the research objects, which are called Decision Making Units (DMUs) in the DEA method. These DMUs are the world's 20 largest automakers by volume in 2015. Then, the choosing of appropriate input and output variables was done, to complete the research data.

Part 3. Data analysis: The collected data were checked for the correlation coefficient, to ensure the relationship between input and output variables follows the isotonicity condition. If their correlation coefficients are zero or negative, the data were re-selected, until they met the positive correlation coefficient requirement. After that, the DEA Malmquist model was applied, to calculate the catch-up index, frontier-shift, and Malmquist index of the DMUs.

Part 4. Results, discussion: In the last part, the results of catch-up index (efficiency change), frontier-shift (technological change), and Malmquist index (total factor productivity change) of the DMUs are evaluated, discussed, and concluded.

3.2. Malmquist Productivity Index

Evaluating the change in total factor productivity of a DMU within two periods is the main purpose of the MPI, being described as the product of catch-up efficiency change and technological change (frontier-shift). Efficiency change is associated with the intensity of attempts of the DMU to achieve any improvements or deterioration in its efficiency, while technological change reflects any changes in the frontiers' efficiency between the periods 1 to 2 [15].

The authors denote that the $\mathrm{DMU_i}$ at the time period 1 is $\left(x_i^1, y_i^1\right)$ and at the time period 2 is $\left(x_i^2, y_i^2\right)$. The efficiency score of the $\mathrm{DMU_i}$ $\left(x_i^1, y_i^1\right)^{t1}$ is measured by the technological frontier t_2: $d^{t2}\left((xi,\ yi)^{t1}\right)$ (t_1 = 1, 2 and t_2 = 1, 2).

To calculate for the catch-up (C), frontier-shift (F), and Malmquist Index (MI), the following formulas can be used [8]:

$$C = \frac{d^2\left((x_i, y_i)^2\right)}{d^1\left((x_i, y_i)^1\right)} \tag{1}$$

$$F = \left[\frac{d^1\left((x_i, y_i)^1\right)}{d^2\left((x_i, y_i)^1\right)}\ x\ \frac{d^1\left((x_i, y_i)^2\right)}{d^2\left((x_i, y_i)^2\right)}\right]^{\frac{1}{2}} \tag{2}$$

$$MI = C\ x\ F = \frac{d^2\left((x_i, y_i)^2\right)}{d^1\left((x_i, y_i)^1\right)}\ x\ \left[\frac{d^1\left((x_i, y_i)^1\right)}{d^2\left((x_i, y_i)^1\right)}\ x\ \frac{d^1\left((x_i, y_i)^2\right)}{d^2\left((x_i, y_i)^2\right)}\right]^{\frac{1}{2}} \tag{3}$$

$$MI = \left[\frac{d^1\left((x_i, y_i)^2\right)}{d^1\left((x_i, y_i)^1\right)}\ x\ \frac{d^2\left((x_i, y_i)^2\right)}{d^2\left((x_i, y_i)^1\right)}\right]^{\frac{1}{2}} \tag{4}$$

From the above formulas, we can see that the DMU's total factor productivity (TFP) reflects the advances or declines of the DMUs in technical and technological innovation efficiency. If the values of C, F, and MI are >1, =0, or <1, it respectively indicates the progress, status quo, and regress in the technical efficiency, technological change, and the total factor productivity of the $\mathrm{DMU_i}$ from period 1 to 2.

3.3. Pearson Correlation Coefficient

The Pearson correlation is widely used in many research studies; it was developed by Karl Pearson and published by Auguste Bravais in 1844. It has a value between −1 and +1, representing the linear dependence of two variables or sets of data, where +1 is total positive linear correlation (when one variable increases in value, the other variable will also increase), 0 is no linear correlation (there is no association between the two variables), and −1 is total negative linear correlation (when one variable increases in value, the other variable will have a decrease in value), as illustrated in Figure 2.

The correlation coefficient formula of Pearson's (r) of two variables (x) and (y) is measured as follows [8]:

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2}\ \sqrt{\sum_{i=1}^{n}(y_i - \overline{y})^2}} \tag{5}$$

where n is the size of the sample; x_i,y_i denotes the individual sample points indexed with i; and $\overline{x} = \frac{1}{n}\sum_1^n x_i$ is the mean of the sample which is analogous for $\overline{y}$.

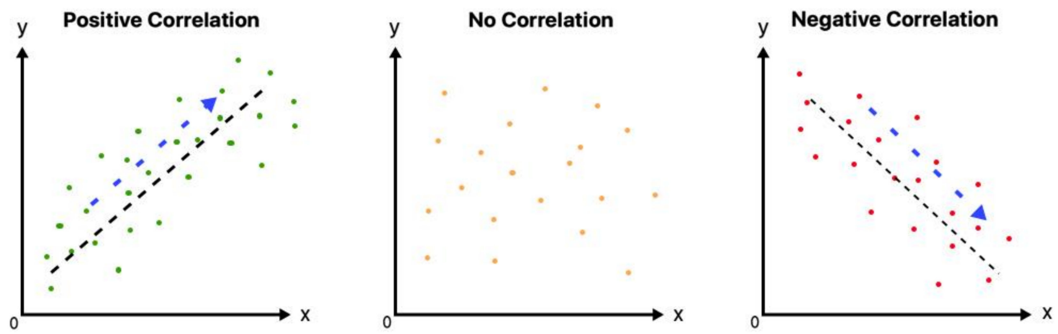

Figure 2. Linear correlation diagrams.

Since the homogeneity and isotonicity are two important DEA data assumptions, these make the correlation test an essential procedure before the application of DEA. This is an assurance that there is an isotonic condition between input and output variables. The input and output data need to have a positive correlation (the values of the output factors should not decrease while the values of the input factors increase); the closer the value to +1, the better positive linear relationship.

3.4. Data Collection

3.4.1. Selection of Decision-Making Units (DMUs)

This study focuses on the performance evaluation of the world's top 20 automakers in terms of production in 2015. They are the 20 automobile manufacturers (of more than 100 global automobile manufacturers) that have a big impact on the global automotive industry, with an annual output of over 1 million units. Out of these 20 automakers, there are 12 from Asia (six from Japan, four from China, one from Korea, and one from India), six from Europe (three from Germany, two from France, and one from the Netherlands), and two from the United States, as listed in Table 1, below.

Table 1. List of 20 global automakers, according to the International Organization of Automobile Manufacturers (OICA) [24].

DMUs	Automakers	Headquarters	Production in 2015 (Cars)	Rank by Productions in 2015
D1	BAIC	Beijing, China	1,169,894	19
D2	BMW	München, Germany	2,279,503	12
D3	Chang'an Auto	Chongqing, China	1,540,133	16
D4	Daimler AG	Stuttgart, Germany	2,134,645	14
D5	Dongfeng Motor	Wuhan, Hubei, China	1,209,296	18
D6	Fiat Chrysler	Amsterdam, Netherlands	4,865,233	7
D7	Ford	Michigan, US	6,396,369	5
D8	General Motors	Michigan, US	7,485,587	4
D9	Honda	Tokyo, Japan	4,543,838	8
D10	Hyundai	Seoul, South Korea	7,988,479	3
D11	Mazda	Hiroshima, Japan	1,540,576	15
D12	Mitsubishi	Tokyo, Japan	1,218,853	17
D13	Nissan	Yokohama, Japan	5,170,074	6
D14	Peugeot	Sochaux, France	2,982,035	11
D15	Renault	Boulogne, France	3,032,652	10
D16	SAIC	Shanghai, China	2,260,579	13
D17	Suzuki	Hamamatsu, Japan	3,034,081	9
D18	Tata Motors	Mumbai, India	1,009,369	20
D19	Toyota	Aichi, Japan	10,083,831	1
D20	Volkswagen	Wolfsburg, Germany	9,872,424	2

3.4.2. Selection of Input/Output Variables

Selecting input and output factors is an important task in employing DEA to measure the efficiency of DMUs. DEA is a complicated technique, wherein that the inputs and outputs have a strong impact on the result. Based from inadequate benefit analysis, determination of the proper number of variables can be neglected. Moreover, currently, there is no precise method in variable selection that must be followed. According to previous studies, the authors found that input variables are financial indicators that the company needs to balance or decrease, while output variables are indicators that the company needs to improve or increase. After thorough study, the researchers decided to choose four input and two output factors, which are stated below:

Input Factors

1. Total Assets (TA): the total amount of assets owned by the automaker second item.
2. Equity (EQ): the higher the equity level of a company, the better access to many debt-based funding. If most assets come from equity, the financial leverage is low, and then equity can be a proxy for financial debt-based assets for companies.
3. Cost of Revenue (CR): the total costs that are directly connected with producing and distributing goods and services to customers of the automaker.
4. Operating Expenses (OE): expenditures incurred in carrying out automaker's day-to-day activities but not directly associated with production, including selling, administrative and general expenses.

Output Factors

1. Revenue (RE): the total receipts that the automaker obtains from selling goods or services.
2. Net Income (NI): the actual profit of the automaker after accounting for all costs, and taxes.

These six important financial indicators play an important role in assessing a company's performance. Every business needs to manage its assets, control its capital well, reduce production and operation costs, and increase its income and profits. The authors limited the input variables to only financial indicators, since the study focused on the aspect of efficiency in terms of financial capabilities. To be able to use these data for the DEA analysis, the authors chose the outputs which are necessarily to be increasing along with the values of the input factors. There must be an isotonic condition between the input and output variables, or else the chosen factors cannot be used. That is the reason why the authors chose these factors as research variables.

3.4.3. Research Data

The 2015–2018 period's data were collected from the automobile manufacturers' annual reports and from information published on their official websites [25]. The unit is calculated in millions of US dollars. Table 2 below shows the statistical data for each year period.

Table 2. Summary of statistics for each year periods.

Year	Statistics	TA	EQ	CR	OE	RE	NI
2015	Max	433,120	152,342	201,230	39,429	247,137	21,259
	Min	13,412.1	5157.75	8011.05	1491.45	10,015.8	1.000
	Ave.	134,650.3	36,800.74	75,644.54	12,096.33	92,420.68	5748.965
	SD	123,220.5	36,012.59	58,281.8	9110.951	70,048.78	4687.882
2016	Max	459,637	151,968	205,131	36,648	257,741	20,986
	Min	13,010	6024	9673.2	1522.8	11,781.3	658
	Ave.	142,609.1	38,525.88	78,302.2	13,096.46	97,175.87	4616.053
	SD	129,059.5	36,322.72	58,893.88	9264.601	72,236.68	4603.454
2017	Max	473,616	158,936	211,055	32,643	258,779	20,481
	Min	13,470	6125.4	10,404.45	1539.3	12,001.8	1.000
	Ave.	148,300.6	41,408.17	80,085.3	12,902.93	99,035.85	8459.098
	SD	132,444.6	39,474.08	60,039.49	8548.417	72,817.91	5008.035
2018	Max	513,959	170,017	216,779	35,803	266,601	22,631
	Min	14,023.35	6936.75	8487.45	1302.3	9944.7	102.15
	Ave.	156,200.6	44,524.12	83,214.39	13,574.66	102,395.2	5283.818
	SD	140,497.7	41,682.19	61,858.42	9347.215	75,298.09	5322.953

D20 in 2015, and D8 and D12 in 2017 have negative values in Net Income (this is an indication that those firms suffered a loss during that year). Since homogeneity is an important aspect of DEA data assumption, the negative values from the raw data need to be adjusted upward, to positive values. After adjustment, the net income of each DMU in 2015 increased by 1538, and in 2017, increased by 3865. This simultaneous change of value does not affect the DEA calculation results.

The process, methods, tools, and research data to carry out this study were discussed above. In the next section, the authors apply the Pearson correlation coefficient testing tool and DEA Malmquist model, to calculate the research data.

4. Results and Discussion

4.1. Correlation Results

In DEA, a variable is a factor that greatly affects the research results. Before using the Malmquist or any model in DEA to process the data, the isotonic condition in between the input and output variables must be met. It only means that the increase in the values of the input variables should not make the values of the output variables decrease [26]. Therefore, the research data must first be validated by using the Pearson correlation, to ensure the isotonic relationship between input and output variables. The value range of the Pearson correlation coefficient is from −1 to +1. The results of the Pearson correlation test are shown in Table 3, below.

Table 3. Coefficients of correlation between variables.

Factors	TA	EQ	CR	OE	RE	NI
			2015			
Total Assets	1.0000	0.9256	0.9556	0.9017	0.9666	0.6036
Equity	0.9256	1.0000	0.8440	0.7933	0.8670	0.6986
Cost of Revenue	0.9556	0.8440	1.0000	0.9070	0.9972	0.5770
Operating Expenses	0.9017	0.7933	0.9070	1.0000	0.9165	0.3494
Revenue	0.9666	0.8670	0.9972	0.9165	1.0000	0.6034
Net Income	0.6036	0.6986	0.5770	0.3494	0.6034	1.0000
			2016			
Total Assets	1.0000	0.9213	0.9507	0.9063	0.9583	0.7981
Equity	0.9213	1.0000	0.8626	0.8061	0.8783	0.8778
Cost of Revenue	0.9507	0.8626	1.0000	0.9227	0.9984	0.7835
Operating Expenses	0.9063	0.8061	0.9227	1.0000	0.9342	0.6172
Revenue	0.9583	0.8783	0.9984	0.9342	1.0000	0.7952
Net Income	0.7981	0.8778	0.7835	0.6172	0.7952	1.0000
			2017			
Total Assets	1.0000	0.9305	0.9554	0.9185	0.9610	0.8320
Equity	0.9305	1.0000	0.8736	0.8142	0.8785	0.8651
Cost of Revenue	0.9554	0.8736	1.0000	0.9374	0.9987	0.7928
Operating Expenses	0.9185	0.8142	0.9374	1.0000	0.9506	0.6963
Revenue	0.9610	0.8785	0.9987	0.9506	1.0000	0.7915
Net Income	0.8320	0.8651	0.7928	0.6963	0.7915	1.0000
			2018			
Total Assets	1.0000	0.9258	0.9476	0.9059	0.9551	0.8739
Equity	0.9258	1.0000	0.8748	0.8093	0.8866	0.9429
Cost of Revenue	0.9476	0.8748	1.0000	0.9341	0.9985	0.8730
Operating Expenses	0.9059	0.8093	0.9341	1.0000	0.9460	0.7973
Revenue	0.9551	0.8866	0.9985	0.9460	1.0000	0.8841
Net Income	0.8739	0.9429	0.8730	0.7973	0.8841	1.0000

Source: calculated by researchers.

The correlation coefficient ranges from 0.3494379 to 1; all are positive correlations. It means that the used data comply with isotropic conditions and can be used for DEA calculations. This also proves that the choice of inputs and outputs is applicable for DEA.

4.2. Catch-Up Index (Technical Efficiency)

The Malmquist productivity index has the components which are used in performance measurement, such as changes in technical, technological, and total factor productivity. The authors present results of efficiency change. The technical effective changes of the DMUs are expressed through the catch-up index shown in the Table 4 and Figure 3.

Table 4. Result of the DMUs' catch-up index.

DMUs	Automaker	2015 ≥ 2016	2016 ≥ 2017	2017 ≥ 2018	Average
D1	BAIC	1.007906519	1.067588827	0.951099081	1.008864809
D2	BMW	1.002200700	0.989942896	1.032516308	1.008219968
D3	Chang'an Auto	0.802806822	1.088698475	0.447817244	0.779774180
D4	Daimler AG	0.930637488	0.851411104	1.006351466	0.929466686
D5	Dongfeng Motor	0.997491449	0.942585562	1.198699708	1.046258907
D6	Fiat Chrysler	0.974202762	1.003801147	0.93822297	0.972075626
D7	Ford	0.969533267	0.772186068	1.272174794	1.004631376
D8	General Motors	1.203162859	0.831481843	1.238505175	1.091049959
D9	Honda	1.017930963	0.991968224	1.268988397	1.092962528
D10	Hyundai	0.985207492	0.839423806	1.003855082	0.942828794
D11	Mazda	1.056287293	1.032101748	0.951842778	1.013410606
D12	Mitsubishi	0.952867583	0.951779377	1.027294947	0.977313969
D13	Nissan	1.103923082	0.869170202	1.230991107	1.06802813
D14	Peugeot	1.002611318	0.97492581	1.064404376	1.013980502
D15	Renault	1.157947517	0.863096113	1.109919469	1.043654366
D16	SAIC	1.048487305	0.876499742	1.046332557	0.990439868
D17	Suzuki	1.197202876	1.053332401	1.097676298	1.116070525
D18	Tata Motors	0.939140968	1.053801742	0.923920449	0.972287719
D19	Toyota	1.004901805	0.692280752	1.479811835	1.058998131
D20	Volkswagen	1.07190144	0.974113	1.12718749	1.057733977
Average		1.021317575	0.936009442	1.070880577	1.009402531
Max		1.203162859	1.088698475	1.479811835	1.116070525
Min		0.802806822	0.692280752	0.447817244	0.77977418

Source: calculated by researchers.

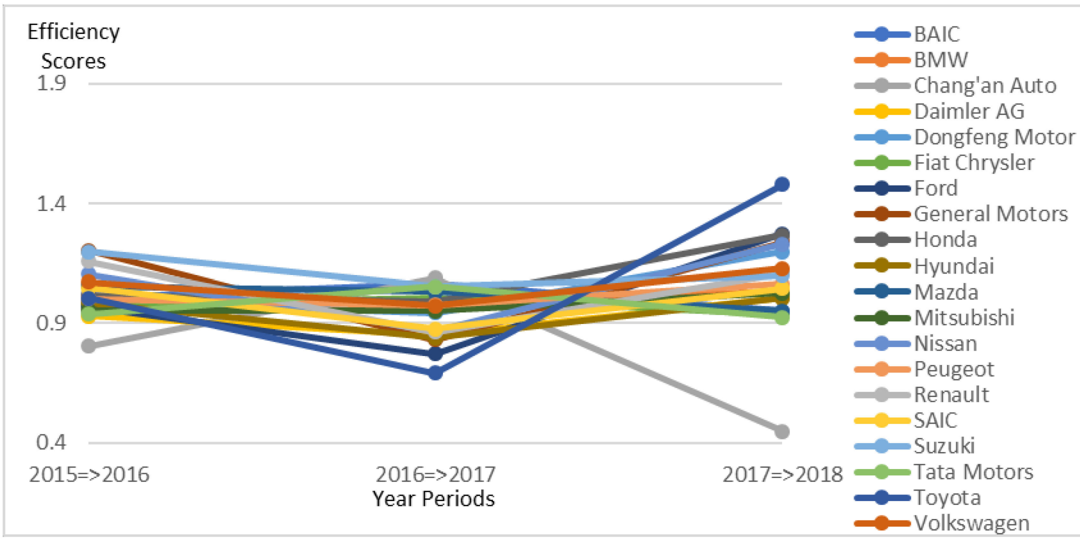

Figure 3. Technical efficiency changes of each DMU.

Catch-up index, with scores >1 and <1, respectively, indicates the progress and regress in technical efficiency of DMUs. Technical efficiency of DMUs tended to decrease in the period 2016–2017 and increase in the 2017–2018 period. The average catch-up = 1.009403 (>1) reflects that the majority (13 DMUs: D1, 2, 5, 7, 8, 9, 11, 13, 14, 15,,17, 19, and 20) achieved technical efficiency in the total research period (2015–2018). D17 (Suzuki) achieved the best and the most stable technical performance, while D3 (Chang'an Auto) had the lowest and the least-stable efficiency performance on average.

During the 2015–2016 period, 12 of the 20 DMUs achieved technical efficiency, with the catch-up index greater than 1. The DMU that had the highest technical efficiency was D8 (General Motors), with a value of 1.203. Meanwhile, D3 had the lowest technical efficiency, at 0.779774180

It is noticeable that, during the period of 2016–2017, most of the DMUs did not achieve progressive technical efficiency (D1, 3, 6, 11, 17, and 18), with catch-up scores greater than 1. D19 (Toyota) was the least-efficient automobile manufacturer in this period, with a score of 0.692. D3 (Chang'an Auto) had an impressive improvement in technical efficiency, being the least-effective producer during the previous period and then becoming the most technically efficient producer in this period.

After the low performance from the previous period, the automakers showed significant improvement in technical efficiency in the next period, 2017–2018. Results show that there are only five out of 20 companies (D1, 3, 6, 11, and 18) that have catch-up values less than 1. Being the worst-performing manufacturer in the previous period, D19 (Toyota) had shown improvement and became the most technically efficient manufacturer in this period, with a catch-up value of 1.47. Surprisingly, D3 (Chang'an Auto) failed to maintain high efficiency and suffered a serious decline in technical efficiency, with a catch-up value of only 0.4478, while the other competitors were above 0.9.

In the list of 20 DMUs, four of them are from China, six from Japan, six from Europe, two from America, one from Korea, and one from India. Among the four Chinese carmakers (D1-BAIC, D3-Chang'an Auto, D5-Dongfeng, and D16-SAIC), the authors noticed, in Figure 4 below, that Dongfeng and SAIC showed improvement in technical efficiency, while Chang'an Auto and BAIC regressed in regard to efficiency change.

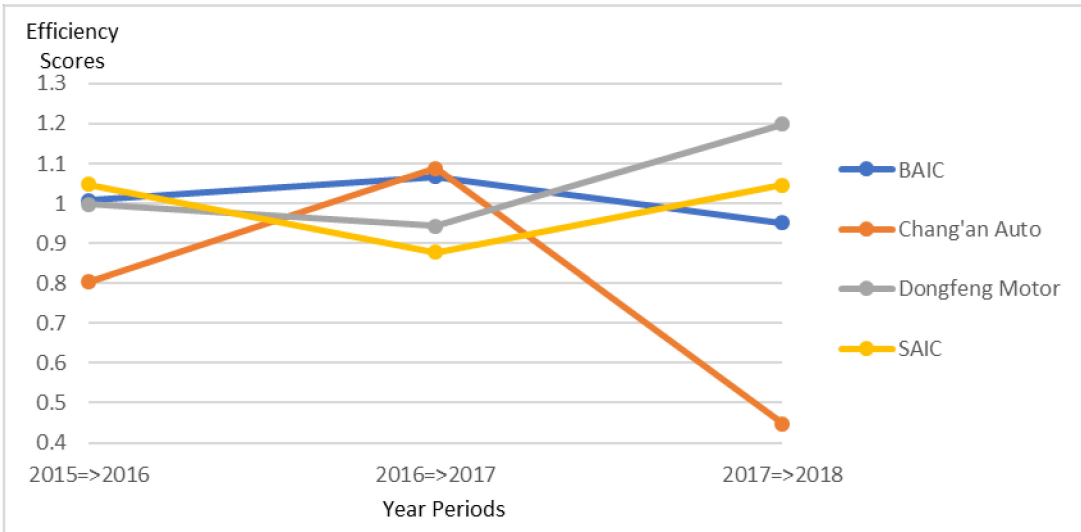

Figure 4. Technical-efficiency changes of Chinese automakers.

After a decline in technical efficiency during the period of 2016–2017, except for Mazda (D11), the remaining five Japanese automakers had a clear improvement, as seen in Figure 5, below. Toyota (D19) showed the most noticeable improvement, by going from being the least-effective manufacturer to becoming superior compared to other competitors.

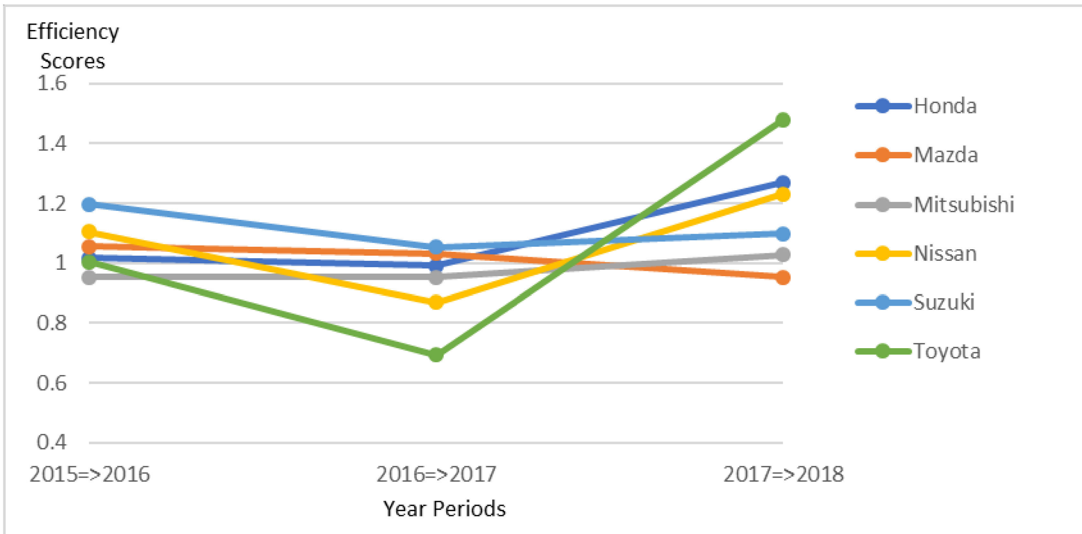

Figure 5. Technical-efficiency changes of Japanese automakers.

Like Japanese automakers, European carmakers also tended to improve their performances after the previous decline. Only one automaker, Fiat Chrysler (D6), showed a degradation in technical efficiency, as seen in Figure 6.

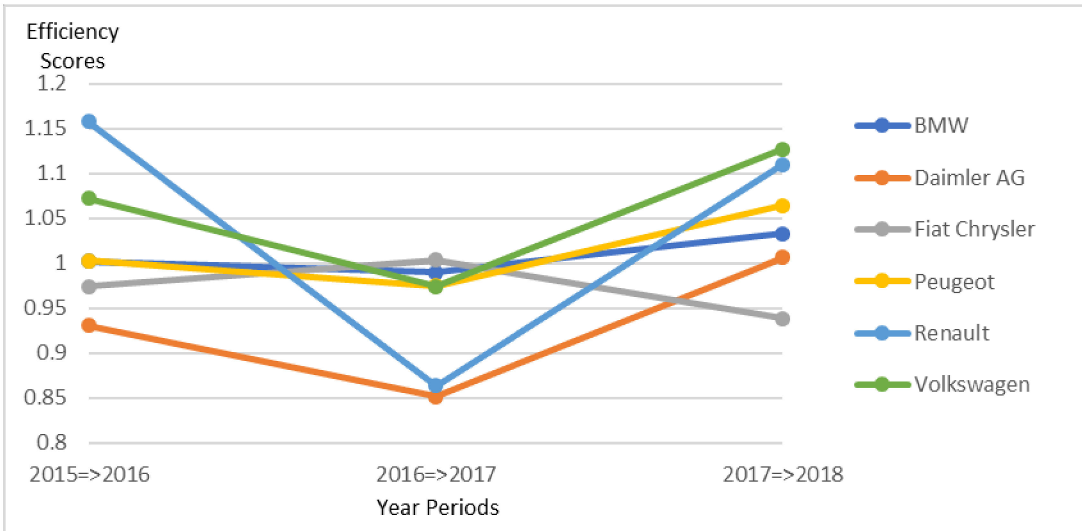

Figure 6. Technical-efficiency changes of European automakers.

Figure 7, below, shows the remaining four manufacturers, Ford, General Motor (from the US), Hyundai (from Korea), and Tata Motors (from India) exhibiting less-significant changes in technical efficiencies.

Despite being less effective than its rival, General Motors (D8), in previous periods, Ford (D7) showed improvement in technical efficiency and even surpassed its rival during the 2017–2018 period. The Korean automaker Hyundai (D10) improved its technical efficiency, and the Indian automaker Tata Motors (D18) showed a regress, despite achieving good performance in the previous 2016–2017 period.

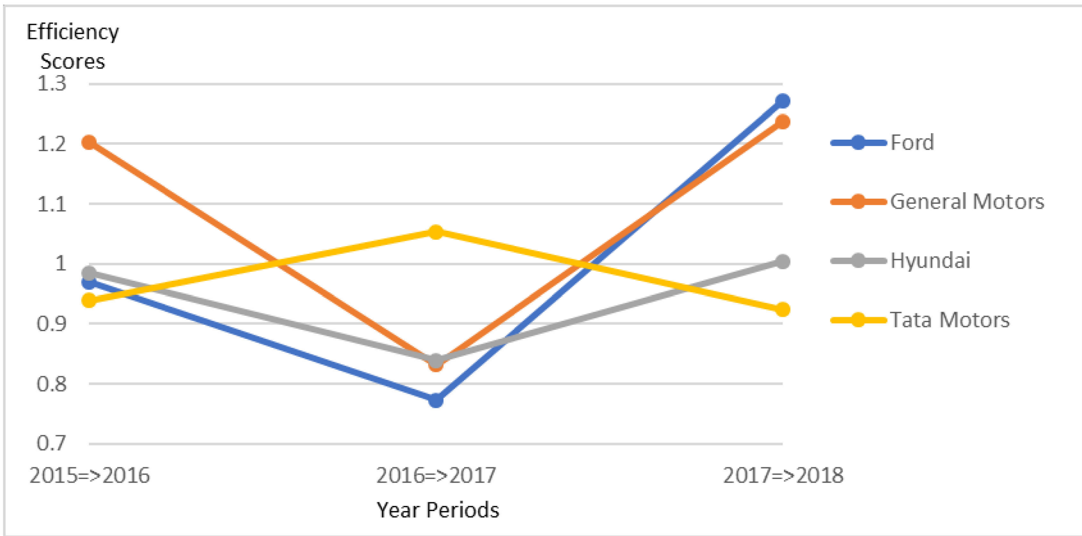

Figure 7. Technical-efficiency changes of US, Korean, and Indian automakers.

4.3. *Frontier-Shift Index (Technological Change)*

The frontier-shift index is applied to measure the efficiency frontiers of DMUs between two periods. Table 5 shows that the technological efficiency of automobile manufacturers increased in the period 2016–2017 and decreased in the period of 2017–2018.

Table 5. Frontier-shift index of the DMUs.

DMUs	Automaker	2015 ≥ 2016	2016 ≥ 2017	2017 ≥ 2018	Average
D1	BAIC	0.836805193	1.546229001	0.588987818	0.990674
D2	BMW	0.934837626	1.076482507	0.868562222	0.9599608
D3	Chang'an Auto	0.620779568	2.104430625	0.566303729	1.0971713
D4	Daimler AG	0.996127981	1.243645099	0.791735446	1.0105028
D5	Dongfeng Motor	0.733741954	1.711266889	0.488457455	0.9778221
D6	Fiat Chrysler	0.98892349	1.130289028	0.805868394	0.975027
D7	Ford	0.861670304	1.333023477	0.681088404	0.9585941
D8	General Motors	0.838888086	1.202999181	0.838415742	0.960101
D9	Honda	0.967083237	1.106332753	0.771206593	0.9482075
D10	Hyundai	0.892240838	1.249043339	0.813506803	0.9849303
D11	Mazda	0.850399789	1.2533984	0.634128384	0.9126422
D12	Mitsubishi	0.859881874	1.112169071	0.725179558	0.8990768
D13	Nissan	0.959916617	1.241455916	0.687654242	0.9630089
D14	Peugeot	0.961643757	1.14347053	0.761186141	0.9554335
D15	Renault	0.855171144	1.416545764	0.630590472	0.9674358
D16	SAIC	0.925493158	1.141159707	0.761752174	0.9428017
D17	Suzuki	0.87126208	1.28910142	0.585370558	0.9152447
D18	Tata Motors	0.873868983	1.205930386	0.635285567	0.9050283
D19	Toyota	0.996099676	1.154084768	0.703886497	0.951357
D20	Volkswagen	1.003309415	1.139756648	0.821471088	0.9881791
Average		0.891407239	1.290040725	0.708031865	0.9631599
Max		1.003309415	2.104430625	0.868562222	1.0971713
Min		0.620779568	1.076482507	0.488457455	0.8990768

Source: calculated by researchers.

Except for D20, the remaining all of the manufacturers (19 out of 20) failed to achieve technological progress in the first period of 2015–2016. However, in the next period (2016–2017), manufacturers made efforts in innovating technology and achieving good results. However, they were not able to maintain this progress in the next period (2017–2018), as all of their frontier-shift indicators were lower than 1, even lower than the 2015–2016 period. This shows that the frontier-shift efficiencies of manufacturers seriously fell down during this period. Due to the low value of technological efficiencies in the periods 2015–2016 and 2017–2018, except for Chang'an Auto (D3) and Daimler AG (D4), the average technological efficiency during the total research period (2015–2018) did not result in a progressive score.

It can be observed in Figure 8 that the automobile manufacturers did not achieve technological progress during the period of 2015–2016. Only D20 (Volkswagen) obtained a frontier-shift index greater than 1, indicating that the development in technology and innovation of the global auto industry have not improved very well and have many limitations. After a period of poor technological performance 2015–2016, manufacturers opted to invest in technology innovation and achieved technological efficiency in the period 2016–2017, especially D1, D3, D5, D7, D10, D11, D15, and D17. However, because technology development has been so fast and developing, manufacturers failed to maintain progress and even severely declined in the next period.

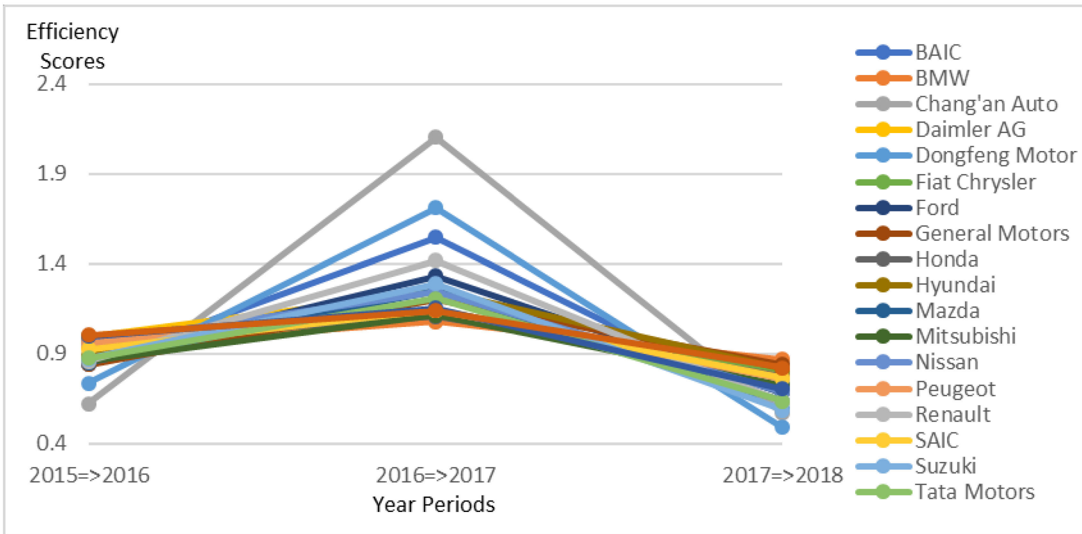

Figure 8. Technical-efficiency frontier of the DMUs.

Figure 9, below, shows the frontier-shift scores of automobile manufacturers in the period of 2017–2018. During this period, the manufacturers with low efficiencies ($F < 0.6$) were Dongfeng, Chang'an Auto, BAIC (manufacturers from China), and Suzuki (Japan). Manufacturers such as Renault, Mazda, Tata Motors, Ford, and Nissan also had a low performance ($F < 0.7$). BMW, General Motors, Volkswagen, Hyundai, and Fiat Chrysler had better technological efficiency than the rest, with $F > 0.8$. Thus, it can be seen that, in this period, manufacturers from Asia, especially China, had a more serious decline in technological efficiency than European and American automobile manufacturers. The simultaneous decline in technological efficiency of all 20 automobile manufacturers shows a close correlation with the decline in global automobile production in this period of 2017–2018.

In terms of technological efficiency, it can be seen that the automakers show a common trend, increasing in the second phase and declining in the remaining two periods, showing that no manufacturer performed a stable technological efficiency or took any lead in the race to technology development and innovation. It only shows that the technology playground in the global automotive industry is highly competitive and holds so much potential for all manufacturers.

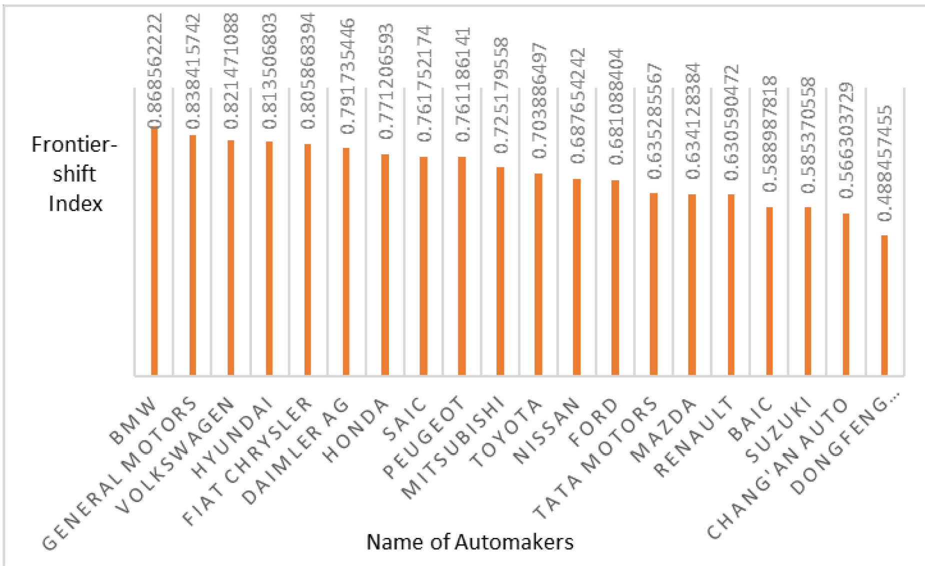

Figure 9. Frontier-shift index of automakers in 2017–2018 period.

4.4. Malmquist Productivity Index (MPI)

MPI is one very valuable component in evaluating the performance of global automobile manufacturers. It measures the change in total factor productivity of DMUs at a certain interval periods and is the product of catch-up index (technical efficiency) and frontier-shift (technological change).

As shown in Table 6 and Figure 10, the average Malmquist index of DMUs less than 1 (0.9632678) indicates a regression in the total productivity growth of the DMUs. The total performance of most DMUs increased in the period 2016–2017 and significantly decreased in the 2017–2018 period.

Table 6. Malmquist productivity index of the DMUs, from 2015 to 2018.

DMUs	Automaker	2015 ≥ 2016	2016 ≥ 2017	2017 ≥ 2018	Average
D1	BAIC	0.84342141	1.650736804	0.560185773	1.0181147
D2	BMW	0.936894924	1.06565621	0.896804659	0.9664519
D3	Chang'an Auto	0.498366072	2.291090413	0.253600576	1.0143524
D4	Daimler AG	0.927034042	1.058853247	0.796764127	0.9275505
D5	Dongfeng Motor	0.731901325	1.613015462	0.585513808	0.9768102
D6	Fiat Chrysler	0.963411995	1.134585423	0.756084238	0.9513606
D7	Ford	0.835418025	1.029342158	0.8664635	0.9104079
D8	General Motors	1.009318988	1.000271976	1.038382236	1.0159911
D9	Honda	0.984423971	1.097446936	0.978652219	1.0201744
D10	Hyundai	0.879042358	1.048476714	0.816642939	0.9147207
D11	Mazda	0.898266491	1.293634679	0.603590522	0.9318306
D12	Mitsubishi	0.819353562	1.058539585	0.744973296	0.8742888
D13	Nissan	1.05967411	1.079036489	0.846496257	0.995069
D14	Peugeot	0.964154915	1.114798933	0.81020986	0.9630546
D15	Renault	0.990243303	1.222615142	0.699904642	0.970921
D16	SAIC	0.970367828	1.000226189	0.797046101	0.9225467
D17	Suzuki	1.043077467	1.357852294	0.642547387	1.0144924
D18	Tata Motors	0.820686163	1.270811541	0.586953327	0.892817
D19	Toyota	1.000982362	0.798950672	1.04161957	0.9471842
D20	Volkswagen	1.075448807	1.110251768	0.925951934	1.0372175
Average		0.912574406	1.214809632	0.762419348	0.9632678
Max		1.075448807	2.291090413	1.04161957	1.0372175
Min		0.498366072	0.798950672	0.253600576	0.8742888

Source: calculated by researchers.

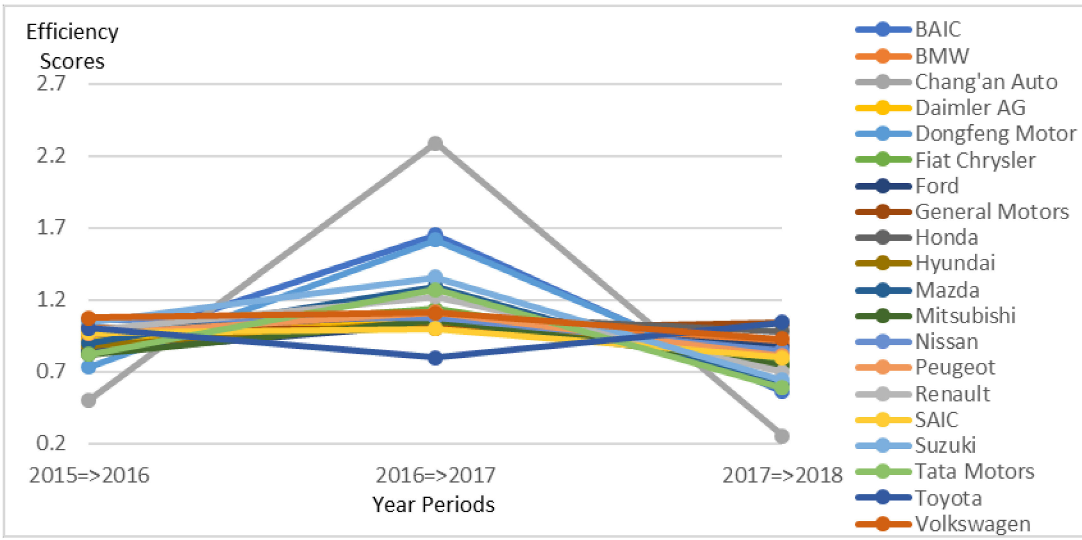

Figure 10. Total-factor-productivity change.

In the period of 2015–2016, most of the DMUs performed inefficiently, with the MPI less than 1, only five automakers, namely General Motors (G.M.), Nissan, Suzuki, Toyota, and Volkswagen, achieved progress in total factor productivity.

After performing low efficiency in the 2015–2016 period, car producers improved their productivity and got a good performance. This can be seen by the positive MPI values of DMUs in the next period, 2016–2017. Only D19 (Toyota) did not achieve an efficient performance during this period, with an MPI of 0.7989.

However, the manufacturers could not maintain this progressive performance for the next period, 2017–2018. The productivity scores of automakers even declined very badly, having an average value of only 0.762. The lowest index of 0.2536 belongs to D3 (Chang'an Auto), meaning that it was the least-efficient producer at this period. The two occasional outstanding automakers that achieved a good performance in this period were D8 (General Motors) and D19 (Toyota), with the MPI equal to 1.0383 and 1.0416, respectively.

Although DMUs had a great improvement and performance in the period 2016–2017, the performance in the other two periods were poor (especially in the 2017–2018 period), resulting in 14 out of 20 DMUs having a low-efficiency performance during the research period of 2015–2018 (total average MPI less than 1). Among 20 automotive manufacturers, General Motors is the automaker that had the most stable performance in all stages (all MPI values were greater than 1). Despite the inefficient performance in the 2017–2018 period, Volkswagen is still the best-performing automaker in the total research period, with an average MPI value of 1.037. Volkswagen is followed by Honda, BAIC, General Motor, Suzuki, and Chang'an Auto. In contrast, Mitsubishi and Tata Motors were the worst-performing automakers, with the lowest average MPI values.

Figure 11 presents the total factor productivity change of Asian automakers over the research period, 2015–2018. In the figure, there is a big difference in the performance between the Asian manufacturers. Chinese manufacturers have the biggest fluctuation in performance. Among four Chinese automakers, namely D1 (BAIC), D3 (Chang'an Auto), D5 (Dongfeng), and D16 (SAIC), SAIC was more stable compared to others in terms of performance; the remaining automakers showed big fluctuations, with performances that increased rapidly but fell drastically afterward. It can be recognized that Chinese car manufacturers have still not improved the stability in production efficiency and are still struggling to stabilize their production performance.

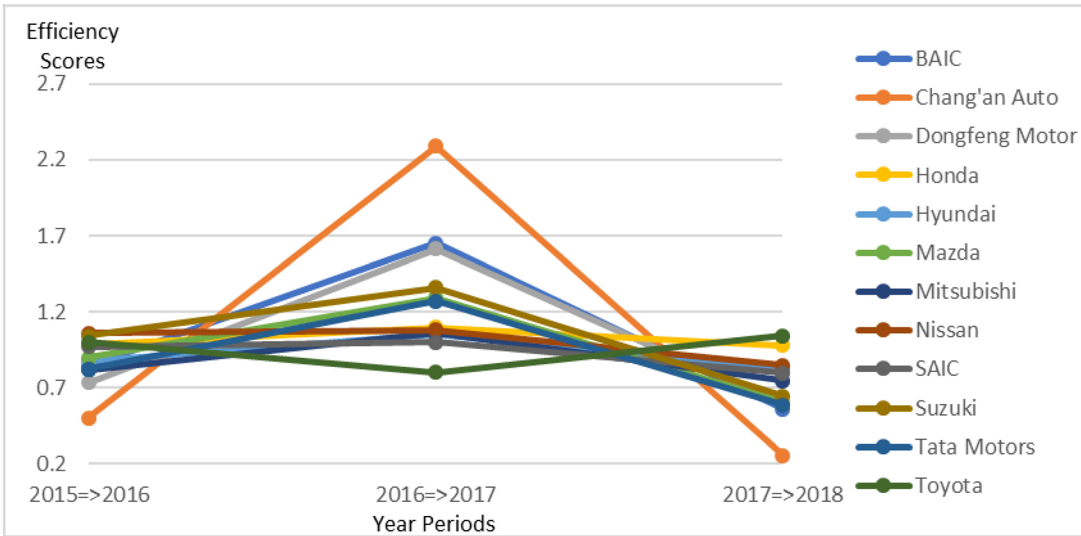

Figure 11. Total-factor-productivity change of Asian automakers.

For Japanese automakers, Toyota (D19) is the manufacturer with the best breakthrough from the least-efficient manufacturer in the second phase to become the only manufacturer to achieve progressive performance in the 2017–2018 period. Honda (D9) shows a stable performance compared to other Japanese companies and other Asian manufacturers. In contrast, Mazda (D11) and Suzuki (D17) need more stability in performance. The other two Asian car producers, Korea's Hyundai (D10) and India's Tata Motors (D18), do not have a stable performance, especially in the 2017–2018 period. The Indian automobile manufacturers demonstrated very poor performance during the 2017–2018 period, lagging behind the three Chinese automobile manufacturers.

As gleaned in Figure 12, there is no significant difference in total factor productivity between the European and American automobile manufacturers. Thus, it can be seen that the performance of European and American manufacturers does not have major fluctuations compared to Asian manufacturers. During the first phase (2015–2016), only Volkswagen (D20) and General Motors (D8) achieved the total factor productivity, while Ford (D7) was the least-efficient producer during this period. Like the Asian companies, European–American automobile manufacturers showed increasing growth in the year 2016–2017. All of the eight European–American manufacturers achieved total factor productivity in this period. Unfortunately, only General Motors was able to maintain this good performance up to the next period, 2017–2018. It is also noticeable that the most unstable manufacturer in terms of performance is Renault (D15). This is due to the automaker's progress on the second-phase performance but fell sharply in the final stage. In contrast to Renault, General Motor is the most stable producer in terms of performance; even when other manufacturers declined in performance, it not only maintained, but also increased, in its performance.

In general, Honda is the only Asian automaker with the best performance, while Volkswagen and General Motors are from Europe–America. Asian automobile manufacturers, especially Chinese automakers, have made breakthrough performances during the 2016–2017 period, in terms of productivity. However, since the productivity efficiencies are not stable, they lost the race in the next period, 2017–2018. Thus, Asian manufacturers—China in particular—need to stabilize their production performance, in order to compete with European manufacturers. Based on the technical, as well as the technology, growth trend of the 20 automobile manufacturers, it can be seen that they still have not balanced the technical efficiency and technological efficiency. Typically, in the period of 2016–2017, when they improved technological change, the technical efficiency regressed. Moreover, the manufacturers were able to improve their technical efficiency, but they were faced with challenges in the technological-innovation aspects, during the period of 2017–2018. Therefore, improving production performance is about making a balance between technical efficiency and technological change; and these two aspects can be developed simultaneously

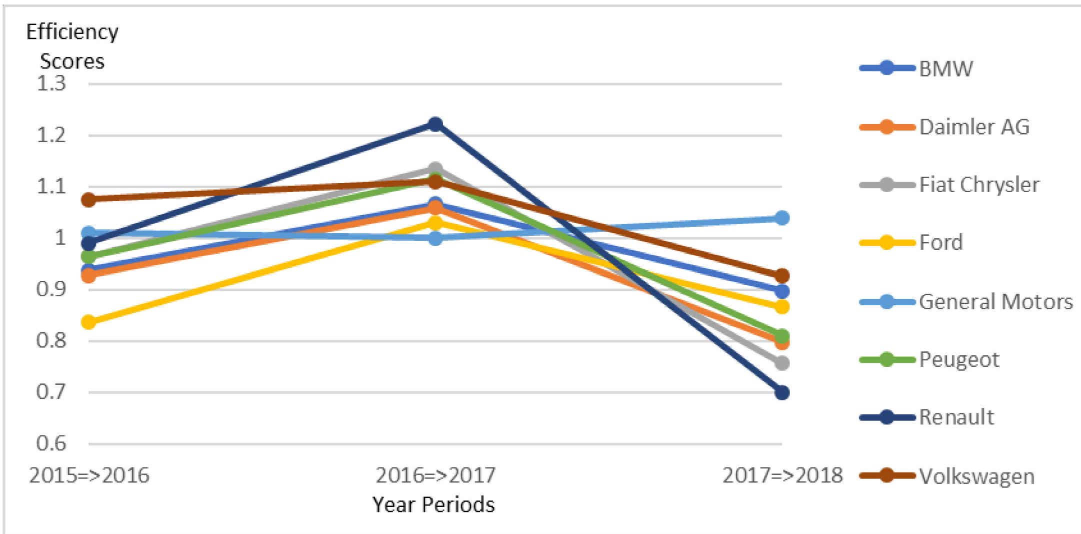

Figure 12. Total-factor-productivity change of European–American automakers.

5. Conclusions

This study illustrates the results of technical efficiency, technological progress, and the total factor productivity of automakers in the four-year periods. Findings show that, after a period of slight decline, most manufacturers have gradually improved their technical efficiency, which somehow leads to technical progress. Suzuki turned out to be the best and most stable manufacturer in terms of technical efficiency, while Chang'an Auto needs more improvement in this aspect. In terms of technological progress, most manufacturers have an unstable performance, especially the Chinese automakers. This regress in performance is also noticed in the study conducted by Imran et al. [27] wherein the export performance of Chinese automotive sector is the main scope. Exportation of automobile units affects the revenue and income of the company in which this paper uses as variables.

Although automakers had a breakthrough in innovation and achievement, as they were able to perform efficiently during the 2016–2017 period, this was not maintained, and they even had a big regression of technological efficiency in the next period. It only affirms that the technology arena in the global automotive industry is highly competitive and shows so much potential for all automakers, since none of them is taking the lead. However, Fathali et al. [28] discussed that there is no strong empirical and theoretical evidence that competition is a major driving force to improvement in technology and innovation. Therefore, whatever the kind of competitive environment the automotive industry is in, there will be continuing technological and innovative development.

Since the total factor productivity is the product of technical efficiency and technological efficiency, manufacturers must balance the development to both technical and technological efficiency, to be able to achieve a progressive outcome. Based on the results, only General Motors achieved a Malmquist index greater than 1 in all year periods. This implies that this manufacturer is the best and most stable automaker among the others. Mitsubishi and Tata Motors are the automakers with the lowest performance on average. The results also show that there is less variation in total factor productivity of European–American producers than Asian manufacturers. The year 2017–2018 is the period when automobile output dropped suddenly after a phase of growth. It is also the period when the technological efficiency index of all 20 automakers significantly declined compared to the previous period, confirming the influence of technological changes to this fluctuation. Therefore, automobile manufacturers need to focus on handling their technology and innovation properly, to avoid the occurrence of a second automobile crisis. This is not in reference to any oil crisis, but a possible industry 4.0 crisis.

This study applied the DEA Malmquist model to evaluate the performance of the world's top 20 automakers over the period of 2015–2018, based on input and output variables, which are very important financial indicators. Based on results, the performance of the world's top 20 automobile manufacturers in terms of technical efficiency, technological efficiency, and total factor productivity not only indicates the overall picture of the world automobile industry but also provides a comparative performance of manufacturers from different countries and continents. The study presented an overview of the Chinese, Japanese, Asian, or European–American automobile industries. Therefore, this can be a valuable reference for car managers, policy makers, or investors for automobile management, investment, and development decisions. Moreover, this study can be used as a guide for automobile manufacturers to form strategic alliance with one another. Wang et al. [29] strongly recommends that the manufacturers in the automobile industry form a strategic alliance with one another, given that there will be an extensive analysis of companies' performances before forming one in which the DEA is a very effective tool. In addition, the study also contributes to the application of the data envelopment analysis method, specifically the Malmquist model in organizational performance measurement, and is a worthy document for the studies of global automotive industry, as well as other fields.

However, the study has several limitations that must be considered. First, the results of this study depend on the value of the input and output variables, which are financial in nature. The results indicated in this study is not applicable or relatable to any other type of industry, even those that are a little related to automobiles, such as the petroleum or fuel industry. However, this study can also be an additional reference, like the other studies cited in this paper. For future studies, the authors must make some modifications in the variables used and then compare the results, to provide a more objective research result. It can also be recommended to improve this kind of study by integrating several input and output factors, such as total number of units produced; undesirable outputs, such as total number of defective units being recalled; and other non-financial variables. Eilert et al. [30] described how the volume of recalled automotive products can somehow affect the sales of the firms, as it may hurt their brand reliability and company's reputation. Research and development expenditure can also be a factor for future studies. Hashmi and Biesebroeck [31] pointed out that the industry leader's aspect of innovation is greatly declining in the efficiency of the automotive firms lagging behind. They mentioned that highly focusing on efficiency leads to an increase in innovation. It will be interesting to know the effects of R&D in the efficiency level of automotive firms. Second, this study focuses on evaluation of the performance from the world's 20 largest automakers. Involvement of other automakers is recommended, in order to give a general overview of the industry performance. Finally, this study is based on a quantitative approach, using DEA Malmquist model, where some external factors are not being considered. The combination with qualitative research will be a worthwhile research direction to more fully evaluate the performance of the automobile manufacturers.

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References

1. Humphrey, J.; Memedovic, O. The global automotive industry value chain: What prospects for upgrading by developing countries. In *UNIDO Sectorial Studies Series Working Paper*; UNIDO: Vienna, Austria, 2003.

2. Kallstrom, H. "Why the automotive industry generates employment". *Market Realist*, 5 February 2015. Available online: https://marketrealist.com/2015/02/automotive-industry-generates-employment/ (accessed on 11 September 2019).
3. Charnes, A.; Cooper, W.W.; Rhodes, E. Measuring the efficiency of decision making units. *Eur. J. Oper. Res.* **1978**, *2*, 429–444. [CrossRef]
4. Martín, J.C.; Roman, C. An application of DEA to measure the efficiency of Spanish airports prior to privatization. *J. Air Transp. Manag.* **2001**, *7*, 149–157. [CrossRef]
5. Kulshreshtha, M.; Parikh, J.K. Study of efficiency and productivity growth in opencast and underground coal mining in India: A DEA analysis. *Energy Econ.* **2002**, *24*, 439–453. [CrossRef]
6. Leachman, C.; Pegels, C.C.; Shin, S.K. Manufacturing performance: Evaluation and determinants. *Int. J. Oper. Prod. Manag.* **2005**, *25*, 851–874. [CrossRef]
7. Pilyavsky, A.; Staat, M. Efficiency and productivity change in Ukrainian health care. *J. Product. Anal.* **2008**, *29*, 143–154. [CrossRef]
8. Wang, C.N.; Nguyen, N.T.; Tran, T.T. Integrated DEA models and grey system theory to evaluate past-to-future performance: A case of Indian electricity industry. *Sci. World J.* **2015**, *2015*, 638710. [CrossRef]
9. Chandraprakaikul, W.; Suebpongsakorn, A. Evaluation of logistics companies using data envelopment analysis. In Proceedings of the 2012 4th IEEE International Symposium on Logistics and Industrial Informatics, Smolenice, Slovakia, 5–7 September 2012; pp. 81–86.
10. Yuan, L.N.; Tian, L.N. A new DEA model on science and technology resources of industrial enterprises. In Proceedings of the 2012 International Conference on Machine Learning and Cybernetics, Xian, China, 15–17 July 2012; Volume 3, pp. 986–990.
11. Ren, J.; Tan, S.; Dong, L.; Mazzi, A.; Scipioni, A.; Sovacool, B.K. Determining the life cycle energy efficiency of six biofuel systems in China: A Data Envelopment Analysis. *Bioresour. Technol.* **2014**, *162*, 1–7. [CrossRef]
12. Chang, Y.T.; Zhang, N.; Danao, D.; Zhang, N. Environmental efficiency analysis of transportation system in China: A non-radial DEA approach. *Energy Policy* **2013**, *58*, 277–283. [CrossRef]
13. Bjurek, H. The Malmquist total factor productivity index. *Scand. J. Econ.* **1996**, *98*, 303–313. [CrossRef]
14. Fuentes, R.; Lillo-Bañuls, A. Smoothed bootstrap Malmquist index based on DEA model to compute productivity of tax offices. *Expert Syst. Appl.* **2015**, *42*, 2442–2450. [CrossRef]
15. Färe, R.; Grosskopf, S.; Norris, M.; Zhang, Z. Productivity growth, technical progress, and efficiency change in industrialized countries. *Am. Econ. Rev.* **1994**, *84*, 66–83.
16. Fulginiti, L.E.; Perrin, R.K. LDC agriculture: Nonparametric Malmquist productivity indexes. *J. Dev. Econ.* **1997**, *53*, 373–390. [CrossRef]
17. Odeck, J. Assessing the relative efficiency and productivity growth of vehicle inspection services: An application of DEA and Malmquist indices. *Eur. J. Oper. Res.* **2000**, *126*, 501–514. [CrossRef]
18. Chen, Y. A non-radial Malmquist productivity index with an illustrative application to Chinese major industries. *Int. J. Prod. Econ.* **2003**, *83*, 27–35. [CrossRef]
19. Sharma, S. A study on Productivity Performance of Indian Automobile Industry: Growth Accounting Analysis. 2006. Available online: https://pdfs.semanticscholar.org/a5cb/4cc8dd07746b84cc3204551d7741d84f9af8.pdf/ (accessed on 15 September 2019).
20. Liu, F.H.F.; Wang, P.H. DEA Malmquist productivity measure: Taiwanese semiconductor companies. *Int. J. Prod. Econ.* **2008**, *112*, 367–379. [CrossRef]
21. Mazumdar, M.; Rajeev, M. *A Comparative Analysis of Efficiency and Productivity of the Indian Pharmaceutical Firms: A Malmquist-Meta-Frontier Approach*; Institute for Social and Economic Change: Bangalore, India, 2009.
22. Wang, C.N.; Chang, Y.L.; Huang, Q.H.; Wang, C.H. Assessment on intellectual capital management for Taiwanese pharmaceutical industry: Using GRA and MPI. *Afr. J. Bus. Manag.* **2011**, *5*, 2950.
23. Chang, H.; Choy, H.L.; Cooper, W.W.; Ruefli, T.W. Using Malmquist Indexes to measure changes in the productivity and efficiency of US accounting firms before and after the Sarbanes–Oxley Act. *Omega* **2009**, *37*, 951–960. [CrossRef]
24. OICA. Available online: http://www.oica.net/wp-content/uploads/ranking2015.pdf/ (accessed on 15 September 2019).
25. Morningstar. Available online: https://www.morningstar.com/ (accessed on 18 September 2019).
26. Wang, J. Pearson correlation coefficient. In *Encyclopedia of Systems Biology*; Springer: New York, NY, USA, 2013; p. 1671.

27. Imran, M.; Jian, Z.; Urbański, M.; Nair, S.L.S. Determinants of firm's export performance in China's automobile industry. *Sustainability* **2018**, *10*, 4078. [CrossRef]
28. Fathali, A. Examining the impact of competitive strategies on corporate innovation: An empirical study in automobile industry. *Int. J. Asian Soc. Sci.* **2016**, *6*, 135–145. [CrossRef]
29. Wang, C.N.; Nguyen, X.T.; Wang, Y.H. Automobile industry strategic alliance partner selection: The application of a hybrid DEA and grey theory model. *Sustainability* **2016**, *8*, 173. [CrossRef]
30. Eilert, M.; Jayachandran, S.; Kalaignanam, K.; Swartz, T.A. Does it pay to recall your product early? An empirical investigation in the automobile industry. *J. Mark.* **2017**, *81*, 111–129. [CrossRef]
31. Hashmi, A.R.; Biesebroeck, J.V. The relationship between market structure and innovation in industry equilibrium: A case study of the global automobile industry. *Rev. Econ. Stat.* **2016**, *98*, 192–208. [CrossRef]