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Supply Chain Efficiency Measurement to Maintain Sustainable Performance in the Automobile Industry

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Abstract: The automobile industry is set to undergo a structural transformation in the progress toward next-generation industries that involve autonomous vehicles and connected cars. Thus, supply chain management has become increasingly important for corporate competitiveness. This study aims to identify opportunities for improving supply chain performance by quantifying suppliers' impact on the supply chain. An analysis was conducted in two phases. First, the efficiency of 139 partners that supply automobile components to the Hyundai Motor Company was measured using the Charnes–Cooper–Rhodes model, while the efficiency of Hyundai Motor Company's 540 supply chains comprising partners, subsidiaries, and parent companies was measured using the network epsilon-based measure model. Second, the relationship between the partner efficiency and the supply chain efficiency was analyzed using the Mann–Whitney U test and the Tobit regression model. The results showed that efficient operation of partners hampers the efficiency of the total supply chain. Thus, there may be several partners that are not committed to quality improvement, while the Hyundai Motor Company seeks to promote quality management through win–win cooperation with partners. Consequently, automakers must review their partner management system, including the evaluation criteria and the incentive system.

Keywords: automobile industry; efficiency analysis; supply chain management; supplier selection; network DEA; epsilon-based measure

1. Introduction

The current automobile industry is undergoing structural changes because of its convergence with cutting-edge information and communication technologies—such as artificial intelligence and the Internet of Things, along with big data—in order to produce next-generation automobiles. To achieve sustainable competitiveness and maximize operational efficiency, the importance of the supply chain has been further emphasized [1]. The systematic management of the supply chain requires activities such as demand forecasting, production planning and scheduling, procurement, inventory management, and logistics to be managed at an integrated supply chain level, rather than the individual company level [2].

Over the last three decades, studies on supply chain management have traditionally focused on a cooperative supply chain and analyzed the effects of cooperation within the supply chain on the performance improvement. Such research has incorporated transaction cost theory, resource-based theory, knowledge-based theory, and game theory [1] for case studies on Toyota, Hewlett Packard Enterprise, and Walmart among others [3–5]. In addition, studies on the establishment of an efficient and sustainable supply chain system have been actively conducted [6–9].

Most of the extant literature has examined the supply chain in its simplest form and identified the relationship between the buyer–supplier partnership and supply chain performance.

Nevertheless, they are limited in their evaluation of supply chain performance using the efficiency and effectiveness of individual companies. The measurement of supply chain performance must be holistically conducted, rather than being focused on the individual level. This is because in conditions where a conflict of interests arises between supply chain players, an efficient operation for one player may lead to an inefficient operation for another player in the supply chain. This would ultimately hamper the efficiency of the entire supply chain [10]. Therefore, to assess the supply chain performance, the nature of and interactions within the supply chain network all need to be taken into consideration in order to integrate and adjust the performance of the supply chain players [11].

The automobile industry in Korea has a top-down (vertical) structure, where automakers exercise power over partners, which is unlike that in the U.S., where automobile components suppliers have grown independently [12]. Hyundai and Kia Motors occupied over 80% of the domestic automobile market, and it leads to a heightened awareness that large conglomerates' opportunistic practices for short-term interests pose serious threats to the survival of small- and medium-sized enterprises (SMEs). As an alternative to this status quo, policies on win–win cooperation that seek to promote mid- to long-term (sustainable) relationships and the mutual growth of automakers and partners have been put forward [13].

The present study aims to empirically analyze the effects of the improved competitiveness of the partners (through win–win cooperation) on the efficiency of the total supply chain. The Hyundai Motor Company has provided financial and technological assistance to their partners, leading them to actively participate in the quality improvement process. However, without integrating the supply chain, such polices are likely to cause inefficiency in the overall supply chain. We hypothesized that an efficient partner with high profitability might maintain quality only to the minimum requirement, and thereby disrupt the supply chain performance. This hypothesis was tested through a three-tier supply chain of partners, subsidiaries, and parent companies in the automobile industry. The rest of the paper is organized as follows. Section 2 examines the literature on supply chain management in the automobile industry. Section 3 describes the data envelopment analysis (DEA) model that we build. Section 4 presents data and criteria for variable selection, and summarizes the results obtained from two DEA models that we use to evaluate the efficiency of partners and supply chains, respectively. Section 5 applies the Mann–Whitney U test and the Tobit regression model to the results of the DEA analysis, and discusses the relationship between these two efficiency scores. Section 6 concludes the paper and suggests future directions.

2. Literature Review

Owing to unstable demand and excessive supply, automakers have faced immense competitive pressure. In light of the increasing need for sustainable supply chain management that allows an optimized material flow, various studies have been conducted on the performance evaluation and benchmarking of supply chain [14].

The supply chain is a complex network in which multiple companies distributed across one business process interact with one another. The evaluation of its performance can be defined as a process that measures its efficiency [15]. The most commonly used method to analyze supply chain efficiency is the DEA model, a non-parametric approach that estimates the relative efficiency of decision-making units (DMU) with multiple inputs and outputs [16]. DEA, unlike a typical supply chain optimization model, has an advantage—it does not require unrealistic prior consumption for variables [17]. However, traditional DEA models, such as Charnes–Cooper–Rhodes (CCR) and Banker–Charnes–Cooper (BCC) models, consider the production process of the DMU to be a black box and have been criticized for not clearly identifying the relationship between inputs and outputs. To address this limitation, a network DEA model was developed to divide the production process of the DMU into multiple processes between the divisions and then calculate the efficiency of the entire networked system [18]. The network DEA model can deal with processes in various formats, including serial, parallel, mixed, hierarchical, and dynamic systems [19]. It can be also extended to hybrid models by combining it with other decision-making methods, such as analytic hierarchy process (AHP), stochastic programming, goal programming, and neural networks. Thus, the network

DEA model is used in studies in the banking, aviation, transport, manufacturing (factories), and sports industries; furthermore, the scope of its application continues to gradually expand [20].

In the automobile industry, studies on supply chain management, which also use the DEA method, have primarily analyzed the efficiency of individual automobile component manufacturers in relation to supplier selection. Zeydan et al. [21] used a fuzzy AHP on automobile trunk panel manufacturers to obtain qualitative variables that were then converted into quantitative variables. These were then designated as the outputs of the DEA method to measure the efficiency of suppliers and exclude inefficient suppliers. Ha and Krishnan [22] operated a supplier portfolio by conducting a cluster analysis based on qualitative and quantitative elements obtained from the AHP, neural network, and DEA methods in order to select competitive suppliers among automatic transmission manufacturers. Çelebi and Bayraktar [23] employed a neural network method to process incomplete supplier data of a local automobile assembly plant that imports components from overseas suppliers to establish evaluation criteria shared by all the DMUs. They applied the DEA method to form a partnership with suppliers classified as efficient DMUs to improve operational efficiency.

Several studies have identified the cause of the differences in the efficiency of automobile component manufacturers. Talluri et al. [24] estimated the efficiency of 150 primary suppliers for three major automakers in the U.S.—GM, Ford, and Chrysler—and categorized them into three groups of high, medium, and low according to their efficiency grades. Then, they utilized a Kruskal–Wallis test to detect between-group differences in cost, quality, on-time delivery, flexibility, and innovation variables. The most efficient and least efficient groups showed a significant difference only in cost, indicating that efficient automobile component manufacturers were successful in cost reduction. Manello et al. [25] examined changes in the total factor productivity of numerous companies in the Italian automobile supply chain over a four-year period after the financial crisis. They used a bootstrap DEA method and a Malmquist productivity index analysis and reported that firms concentrating on their core business were more efficient. Moreover, in contrast with SMEs, large conglomerates were located near the efficiency frontier, which hindered them from benefiting from catching-up effects (emulating other companies), and thus allowed productivity improvement only by technological advancements through innovation.

Meanwhile, some studies have suggested a correlation between the automobile component manufacturer–automaker relationship and the supply chain efficiency. Saranga [14] investigated the Indian automobile industry; the author described a case in which a small-scale manufacturer at a low level of the supply chain had to make advanced payments for raw materials and receive after-payment for supplied components. Owing to this difficult financing environment, instead of using automated equipment, the manufacturing process is undertaken manually, which causes inefficiency in the operations of automobile component manufacturers. The study further suggested that, to ensure an efficient supply chain, automakers at high levels of the supply chain must provide those manufacturers with financial and technological support, as well as long-term supply contracts. This would affect the cost reduction and quality improvement of an automobile supply chain. Sadjadi and Bayati [26] applied game theory to the relationship between raw material producers and automobile component manufacturers in a three-tier supply chain (raw materials producers, auto component manufacturers, and automakers). They computed supply chain efficiency in a cooperative game, where all suppliers made efforts to promote the overall efficiency, and then in a non-cooperative game, where a leader pursued maximization of efficiency and a follower made decisions sequentially, taking the efficiency of a leader as a fixed value (Stackelberg model). The results showed that the optimal efficiency of the cooperative game was greater than or equivalent to that of the non-cooperative game.

In supply chain management, decision-making by individual entities affects not only those entities, but also their counterparts, which ultimately determines the efficiency of the total supply chain. However, most previous studies on automobile supply chain have mainly focused on the individual suppliers. In addition, studies have examined the two-tier supply chain comprising automobile component manufacturers and automakers. Few studies have considered a three-tier or higher supply chain. Thus, this study sets a three-tier supply chain comprising partners, subsidiaries, and parent companies. The individual and overall efficiencies of the supply chain are analyzed to verify the impact of individual entities on a supply chain.

3. Methodology

3.1. CCR Model

The DEA method, introduced by Charnes et al. [27], is a linear programming approach that measures the relative efficiency of the homogeneous DMU using the distance from DMU to an efficient frontier. It establishes efficient frontiers, which are a combination of optimal inputs and outputs, based on the observed data. The efficiency score of the DMU is defined as the ratio of a total weighted output to a total weighted input. The weight of the inputs and outputs is estimated as a value that maximizes the efficiency score of the DMU for evaluation, under the constraint that the efficiency score of all DMUs is less than or equivalent to 1.

The DEA method is generally divided into two models—an input-oriented model that minimizes the input at a given output level and an output-oriented model that maximizes the output at a given input level. When a contract for the supply of automobile components concludes, the unit price, quantity, quality standard, and other elements of the components to be produced by a partner are pre-determined. Therefore, we measure the partner efficiency using an input-oriented model. The DMU of the CCR model is a partner, and the efficiency score of an input-oriented CCR model with a certain number of DMUs, n, is calculated as follows:

$$\begin{aligned} &\theta^* = min\ \theta, \\ &\text{s.t.}\ \ \textstyle\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = \theta x_{io}, \\ &\qquad \textstyle\sum_{j=1}^{n} y_{rj}\lambda_j \geq y_{ro}, \\ &\qquad \lambda_j \geq 0,\ s_i^- \geq 0 \quad i = 1, \ldots, m;\ r = 1, \ldots, q;\ j = 1, \ldots, n \end{aligned} \tag{1}$$

where θ^* is the efficiency score of the DMU_0 for evaluation; x_{ij} and y_{rj} are the ith input ($i = 1, \ldots, m$) and the rth output ($r = 1, \ldots, q$) of the jth DMU ($j = 1, \ldots, n$), respectively; λ is the intensity variable and s_i^- is the input slacks; m and q are the number of inputs and outputs, respectively.

The efficiency score of the CCR model θ is obtained considering all inputs and outputs of different divisions that exist in the DMUs. However, the CCR model presents a problem—as it regards the production process within the DMU as a black box, it is inadequate to capture the internal activities among divisions.

3.2. NEBM Model

The network DEA model, unlike traditional DEA models, measures the efficiency of the DMUs by reflecting the production process of converting inputs into outputs in the network structure. In the network DEA model, an output from a process that is used as an input for another process is classified as an intermediate product; the overall efficiency is calculated through an optimization process [19].

The DEA method features two models—a radial model that assumes a proportionate increase of inputs and outputs and a non-radial model that assumes that inputs and outputs change in a non-proportionate manner. However, the CCR model, which is the most typical radial model, does not consider non-radial slacks, while the slack-based measure (SBM) model, which is the most typical non-radial model, does not consider the radial slacks [28]. Therefore, Tone and Tsutsui [29] suggested an epsilon-based measure (EBM) model that integrates radial and non-radial characteristics.

Tone and Tsutsui [30] developed a network slack-based measure (NSBM) model by extending the SBM model to a network structure, while Tavana et al. [15] suggested a network epsilon-based measure (NEBM) model which applied the EBM model to the network structure. The NEBM model takes into account both radial and non-radial slacks of the data. Thus, it can reflect complex attributes of a multilayered supply chain in which multiple divisions interact with one another. Moreover, as only the DMUs in which all divisions are efficient achieve an NEBM efficiency value of 1, the model has a strong discriminatory power between efficient and inefficient DMUs. Figure 1 summarizes the categorization with respect to the DEA approaches we utilize in this study.

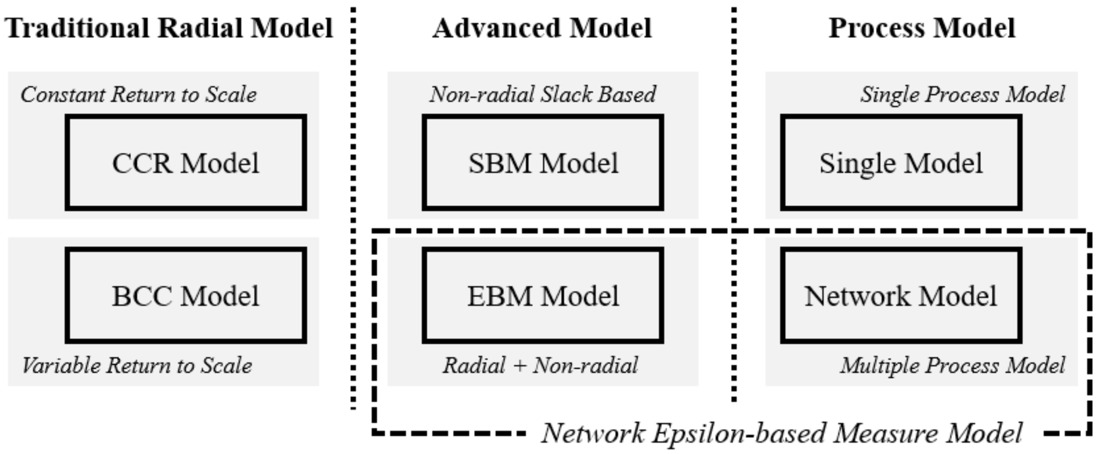

Figure 1. Data envelopment analysis (DEA) method categorization. CCR: Charnes–Cooper–Rhodes; BCC: Banker–Charnes–Cooper; SBM: slack-based measure; EBM: epsilon-based measure.

According to an automobile component supply contract, when partners produce and deliver automobile components, Hyundai Motors' subsidiaries semi-assemble the components to manufacture a module, while its parent companies assemble the modules into a finished automobile. As subsidiaries and parent companies would pursue an efficient operation to maximize the productivity with the supplied components, we measure the supply chain efficiency using an output-oriented model. The DMU of the NEBM model is a supply chain, and its structure is shown in Figure 2. The efficiency score of an output-oriented NEBM model, with n DMUs consisting of k divisions, is calculated as follows:

$$
\begin{aligned}
\gamma^* = {} & \frac{1}{max_{\theta,\lambda,s^+} \sum_{h=1}^{k} W_h(\theta_h + \epsilon_y^h \sum_{r=1}^{q_h} \frac{w_r^{h+} s_r^{h+}}{y_{ro}^h})}, \\
\text{s.t.} \ & \sum_{j=1}^{n} x_{ij}^h \lambda_j^h \le x_{io}^h, \ \ i = 1, \ldots, m_h; \ \ h = 1, \ldots, k, \\
& \sum_{j=1}^{n} y_{rj}^h \lambda_j^h - s_r^{h+} = \theta_h y_{ro}^h, \ \ r = 1, \ldots, q_h; \ \ h = 1, \ldots, k, \\
& z_{f_{(h,h')}0}^{(h,h')} = \sum_{j=1}^{n} z_{f_{(h,h')}j}^{(h,h')} \lambda_j^h \\
& z_{f_{(h,h')}0}^{(h,h')} = \sum_{j=1}^{n} z_{f_{(h,h')}j}^{(h,h')} \lambda_j^{h'}, \ \ f_{(h,h')} = 1, \ldots, F_{(h,h')}, \ \forall (h,h'), \\
& \theta_h \le 1, \ \ h = 1, \ldots, k, \\
& \lambda_j^h \ge 0, \ \ j = 1, \ldots, n; \ h = 1, \ldots, k, \\
& s_r^{h+} \ge 0, \ \ r = 1, \ldots, q_h; \ h = 1, \ldots, k.
\end{aligned}
\tag{2}
$$

where γ^* is the efficiency score of the DMU_0 for evaluation; x_{ij}^h and y_{rj}^h are the *i*th input (*i* = 1, …, m_h) and the *r*th output (*r* = 1, …, q_h) of division *h* (*h* = 1, …, *k*) within the *j*th supply chain (*j* = 1, …, *n*), respectively; λ is the intensity variable and s_r^{h+} is the output slacks in division *h*; m_h and q_h are the number of inputs and outputs of division *h*, respectively; $z_{f_{(h,h')}j}^{(h,h')}$ is an intermediate product transferred from division *h* to division *h*′ within the *j*th supply chain; and the suffix $f_{(h,h')}$ is the number of intermediate products between division *h* and division *h*′ ($f_{(h,h')} = 1, \ldots, F_{(h,h')}$).

w_r^{h+} is the weight of the *r*th output in division *h* that satisfies $\sum_{r=1}^{q_h} w_r^{h+} = 1$. ϵ_y^h is a parameter dependent on the degree of dispersion of the outputs in division *h*. W_h is the weight of division *h* imposed by decision-makers. This study assigned W_h equally to take into account the significance of partners, subsidiaries, and parent companies in a balanced manner.

The first and second constraints are for the inputs and outputs of division h. The third constraint is a linking constraint for intermediate products between division h and division h'; linking constraints include both free links, where the linking activities are freely determined, and fixed links, where they are kept unchanged [30]. In this study, as the divisions of the supply chain are independently operated companies, fixed links were appropriate where all intermediate products are determined outside the discretion of the managers of the companies.

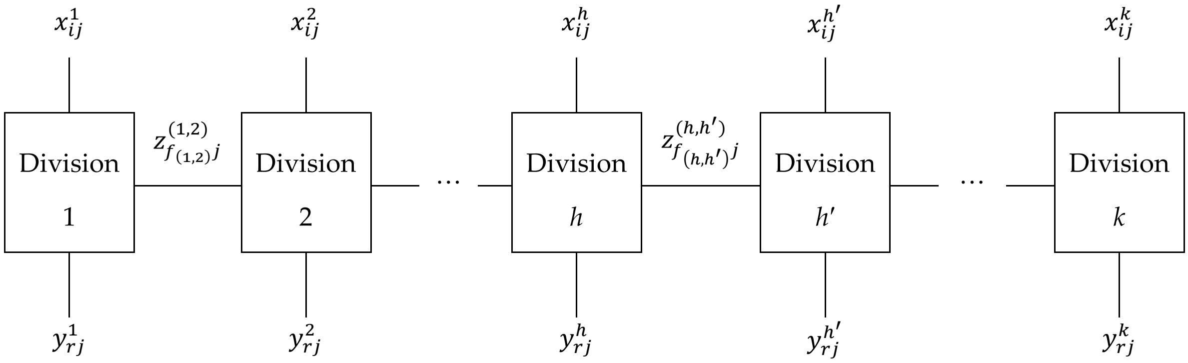

Figure 2. General structure of the supply chain.

The ϵ_y^h value is derived from the dispersion of outputs—the greater the dispersion, the greater the ϵ_y^h value. If the degree of dispersion between the outputs is very low, the ϵ_y^h value becomes 0, and the NEBM model changes into the network Charnes-Cooper-Rhodes (NCCR) model below.

$$\begin{aligned}
&\theta^* = max_{\theta,\lambda} \textstyle\sum_{h=1}^{k} W_h \theta_h,\\
&\text{s.t.}\ \textstyle\sum_{j=1}^{n} x_{ij}^h \lambda_j^h \le x_{io}^h, \quad i = 1,\dots,m_h;\ h = 1,\dots,k,\\
&\textstyle\sum_{j=1}^{n} y_{rj}^h \lambda_j^h \ge \theta_h y_{ro}^h, \quad r = 1,\dots,q_h;\ h = 1,\dots,k,\\
&z_{f_{(h,h')}0}^{(h,h')} = \textstyle\sum_{j=1}^{n} z_{f_{(h,h')}j}^{(h,h')} \lambda_j^h\\
&z_{f_{(h,h')}0}^{(h,h')} = \textstyle\sum_{j=1}^{n} z_{f_{(h,h')}j}^{(h,h')} \lambda_j^{h'}, \quad f_{(h,h')} = 1,\dots,F_{(h,h')},\ \forall (h,h'),\\
&\theta_h \le 1, \quad h = 1,\dots,k,\\
&\lambda_j^h \ge 0, \quad j = 1,\dots,n;\ h = 1,\dots,k.
\end{aligned} \tag{3}$$

On the contrary, if the degree of dispersion between the outputs is very high, the ϵ_y^h value becomes 1, and the NEBM model changes into the NSBM model below [30].

$$\begin{aligned}
&\rho^* = \frac{1}{max_{\lambda,s^+} \sum_{h=1}^{k} W_h \left(1 + \frac{1}{q_h} \sum_{r=1}^{q_h} \frac{s_r^{h+}}{y_{ro}^h}\right)},\\
&\text{s.t.}\ \textstyle\sum_{j=1}^{n} x_{ij}^h \lambda_j^h \le x_{io}^h, \quad i = 1,\dots,m_h;\ h = 1,\dots,k,\\
&\textstyle\sum_{j=1}^{n} y_{rj}^h \lambda_j^h - s_r^{h+} = y_{ro}^h, \quad r = 1,\dots,q_h;\ h = 1,\dots,k,\\
&z_{f_{(h,h')}0}^{(h,h')} = \textstyle\sum_{j=1}^{n} z_{f_{(h,h')}j}^{(h,h')} \lambda_j^h\\
&z_{f_{(h,h')}0}^{(h,h')} = \textstyle\sum_{j=1}^{n} z_{f_{(h,h')}j}^{(h,h')} \lambda_j^{h'}, \quad f_{(h,h')} = 1,\dots,F_{(h,h')},\ \forall (h,h'),\\
&\lambda_j^h \ge 0, \quad j = 1,\dots,n;\ h = 1,\dots,k,\\
&s_r^{h+} \ge 0, \quad r = 1,\dots,q_h;\ h = 1,\dots,k
\end{aligned} \tag{4}$$

The efficiency score of the NEBM model is between the efficiency scores of the NSBM model and the NCCR model ($\rho^*_{NSBM} \leq \gamma^*_{NEBM} \leq \theta^*_{NCCR}$). In this study, the NEBM model assumes constant returns to scale, which leads to a lower number of efficient divisions than the variable returns to scale assumption. For a particular DMU to be NEBM-efficient, all divisions must be NEBM-efficient; this increases the discriminatory power of the NEBM model [15].

4. Data and Variables

Next, we applied the CCR model to 139 partners and the NEBM model to 540 supply chains. Section 4.1 addresses the source of the data. Section 4.2 selects the variables of each model to set the network structure. Section 4.3 presents the results.

4.1. Data

Based on the available data from 2015, 139 partners, six subsidiaries, and two parent companies that participate in a supply chain of the Hyundai Motor Company are selected as the sample; the total number of supply chains which they create is 540. The partners are classified into the Hyundai Motor Group's affiliated and non-affiliated partners. They produce engines, transmission, car seats, automatic control systems, and semiconductors for vehicles. Then, the subsidiaries, which are the Hyundai Motor Group's affiliated companies, semi-assemble the components from partners to manufacture modules and deliver them to the parent companies. The parent companies, Hyundai Motor Company and Kia Motors, install a completed module onto the body frame of automobiles to produce finished automobiles. The two parent companies share major components and produce different lines of automobiles.

The data used in this study are collected from the Data Analysis, Retrieval and Transfer System of the Financial Supervisory Service of Korea (dart.fss.or.kr), Korea Investor's Network for Disclosure (kind.krx.co.kr), KISLINE (www.kisline.com), job posting websites such as Career Catch (www.careercatch.co.kr) and Job Korea (www.jobkorea.co.kr), the Hyundai Motor Company (www.hyundai.com), Korea Auto Industries Coop. Association (www.kaica.or.kr), analysis reports of various securities firms, and finally, official corporate websites and newsletters.

4.2. Variables

The DEA method sets efficient frontiers and evaluates the relative efficiency of the DMUs based only on observed data without any initial assumption for the production function. This makes the selection of adequate inputs and outputs a highly important process. In the DEA method, the validity and discriminatory power of a model exhibit a trade-off. The higher the number of inputs and outputs, the greater the amount of data included in performance evaluation. However, as more DMUs are positioned near efficiency frontiers, the discriminatory power in assessing efficiency decreases [31]. There have been discussions on the methods of minimizing the loss of data and addressing the issue of the discriminatory power. One of these methods is analyzing the correlation between variables to exclude the variables with a strong positive correlation [32,33].

The DMUs of the CCR model are 139 partners. To choose the inputs and outputs, we examine the extant literature on corporate performance evaluation which has applied the DEA method to the automobile industry. Table 1 presents the inputs and outputs used in these studies. With reference to these data, a correlation analysis is carried out to identify the relationship between the number of employees, operating cost, cost of goods sold (COGS), total assets, fixed assets, and net worth and the relationship between total gross sales, pre-tax profit, and operating profit. The variables with a strong correlation are excluded from the inputs and outputs. The inputs for the CCR model comprise the number of employees, operating cost, and fixed assets, while the output is the total gross sales. The number of employees includes regular workers, non-regular workers, and administrative staff. The operating cost is the selling, general and administrative (SG&A) expenses. The fixed assets are property, plant, and equipment. The descriptive statistics of the inputs and outputs are reported in Table 2.

Table 1. Inputs and outputs of previous studies on the automobile industry. DMUs: decision-making units.

Authors (year)	DEA Model Inputs	DEA Model Outputs	Number of DMUs
Saranga (2009) [14]	1. Raw material 1. Labor 3. Capital 4. Sundry expenses	1. Gross income	34
Maritz (2013) [34]	1. Number of employees 1. Operating cost 3. Gross asset	1. Operating income	6
Bhaskaran (2014) [35]	1. Net worth 1. Employment 3. Fixed assets	1. Annual sales	100
Wang et al. (2016) [36]	1. COGS 1. Operating expenses 3. Fixed assets 4. Long-term investment	1. Revenues 1. Total equity 3. Net incomes	20
Sahoo and Rath (2018) [37]	1. Raw materials cost 1. Labor cost 3. Net fixed Asset 4. Energy cost	1. Total gross sales	20

Table 2. Descriptive statistics of inputs and outputs.

	Input Measures		Output Measures	
	Number of Employees	Operating Cost	Fixed Assets	Total Gross Sales
Average	477	35,044,057	146,943,202	446,351,875
Median	350	15,043,376	72,218,825	211,426,813
St. dev.	494	66,448,508	236,959,190	769,312,993
Max	4,307	501,529,108	1,784,196,568	5,558,080,871
Min	47	1,836,184	5,688,211	25,172,709

The DMUs of the NEBM model are 540 supply chains that comprise 139 partners, six subsidiaries, and two parent companies, as shown in Figure 3. The inputs, outputs, and intermediate products of the supply chain should be selected from a comprehensive perspective of the supply chain, not from an individual corporate-level perspective. Most partners are non-affiliated to Hyundai Motor Company; that is, they operate independently, unlike subsidiaries and parent companies which cooperate with each other. As the partners are not part of the Hyundai Motor Group, measuring the efficiency of division h_s would be part of supplier selection.

Weber et al. [38] revealed that price, quality, and delivery performance are key criteria for supplier selection. As reported in Table 3, the studies that have applied the DEA method for supplier selection generally take the price to be the input and the quality to be the output. For delivery performance, delivery time is the input, while order fill rate is the output. In addition, other elements are taken into consideration in evaluating suppliers [39], such as service elements (service standard and responsiveness), technical and production elements (R&D, technology level, and process capability), relationship elements (market cooperation), and administration elements (financial stability). However, since the partners are SMEs with a limited scope of administration, the price is selected as the input, while the quality and delivery performance are selected as the outputs. For the price, the operating profit ratio is used, which indicates the sales margin of the suppliers. For the quality, the score of the quality evaluation system managed by Hyundai Motor Company on its partners is used. For the delivery performance, the finished inventory turnover ratio is used, which are the delivery metrics in the North American automotive supplier supply chain performance study [40].

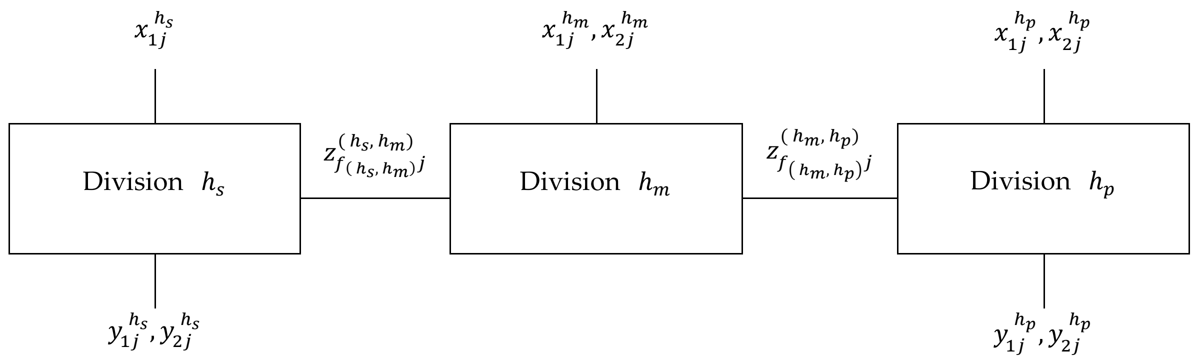

Figure 3. Supply chain structure.

Table 3. Inputs and outputs for supplier selection.

Authors (year)	DEA Model Inputs	DEA Model Outputs
Liu et al. (2000) [41]	1. Price index 1. Delivery performance 3. Distance factor	1. Quality 1. Supplier variety
Talluri et al. (2006) [42]	1. Price	1. Quality 1. Delivery performance
Ramanathan (2007) [43]	1. Total cost	1. Quality 1. Service 3. Technology
Hasan et al. (2008) [44]	1. Net price 1. Lead time	1. Quality 1. Quality benefits 3. Service
Dotoli et al. (2016) [45]	1. Price 1. Lead time 3. Distance	1. Quality 1. Reliability

For subsidiaries and parent companies, the number of employees and operating cost are selected as the inputs, while the total gross sales are selected as the output, with reference to Table 1. As parent companies are automobile export companies, the income from export sales is added as the output for parent companies. Material flow is selected as the intermediate product. The parameters of the supply chain are defined as below, and the descriptive statistics are provided in Table 4.

$x_{1j}^{h_s}$: Operating profit ratio of the h_sth partner in the *j*th supply chain;

$y_{1j}^{h_s}$: Hyundai Motor Company's five-star quality evaluation score of the h_sth partner in the *j*th supply chain;

$y_{2j}^{h_s}$: Finished inventory turnover ratio of the h_sth partner in the *j*th supply chain;

h_s: Numerator of the division in the partners level ($h_s = 1, \ldots, 139$);

$x_{1j}^{h_m}$: The number of employees of the h_mth subsidiary in the *j*th supply chain;

$x_{2j}^{h_m}$: SG&A expenses of the h_mth subsidiary in the *j*th supply chain;

h_m: Numerator of the division in the subsidiaries level ($h_m = 140, \ldots, 145$);

$x_{1j}^{h_p}$: The number of employees of the h_pth parent company in the *j*th supply chain;

$x_{2j}^{h_p}$: SG&A expenses of the h_pth parent company in the *j*th supply chain;

$y_{1j}^{h_p}$: Total gross sales of the h_pth parent company in the *j*th supply chain;

$y_{2j}^{h_p}$: Export sales of the h_pth parent company in the *j*th supply chain;

h_p: Numerator of the division at the parent company level ($h_p = 146, 147$);

$z_{f(h,h')j}^{(h,h')}$: Material flow from division h to division h' ($\forall(\mathrm{h}, h')$).

Table 4. Descriptive statistics of inputs, outputs, and intermediate products.

DMU	Division h_s			Division h_m	
	Input	Outputs		Inputs	
	$x_{1j}^{h_s}$	$y_{1j}^{h_s}$	$y_{2j}^{h_s}$	$x_{1j}^{h_m}$	$x_{2j}^{h_m}$
Average	0.03324	83	0.03741	23	3,137,135
Median	0.03125	81	0.03313	5	765,046
St. dev.	0.02913	3	0.02421	61	8,564,540
Max	0.09906	90	0.12886	605	106,978,039
Min	−0.19030	80	0.00119	0	1,855

DMU	Division h_p					
	Inputs		Outputs		Intermediate	
	$x_{1j}^{h_p}$	$x_{2j}^{h_p}$	$y_{1j}^{h_p}$	$y_{2j}^{h_p}$	$z_{f(h_s,h_m)j}^{(h_s,h_m)}$	$z_{f(h_m,h_p)j}^{(h_m,h_p)}$
Average	17	2,014,454	13,739,946	8,292,159	23	3,137,135
Median	3	426,982	2,905,442	1,716,136	5	765,046
St. dev.	53	5,833,982	39,287,726	23,319,977	61	8,564,540
Max	774	79,056,091	518,284,069	292,719,924	605	106,978,039
Min	0	617	4,355	2,789	0	1,855

4.3. Efficiency Analysis

Table 5 summarizes the efficiency scores of the CCR model for 139 partners and of the NSBM, NEBM, and NCCR models for 540 supply chains. Table 6 also presents descriptive statistics of partners' divisional efficiency scores calculated for each network model. The result of the CCR model shows that only two of the 139 partners obtain an efficiency score of 1. The best practice performers are S083 and S139, which are a reference set for other inefficient DMUs. The CCR efficiency score is generally low; 88 partners have a score below the average (0.3011); S018, S034, and S040 have a score less than 0.1.

The NEBM model is based on the assumptions of (a) constant returns to scale, (b) fixed links, and (c) identical weight for all divisions. In the NEBM model, only the DMUs where all divisions are efficient can be overall efficient [15]. As a result, there is no supply chain with an overall efficiency score of 1. N043, N0245, and N0281 have the highest efficiency score (0.9866); we can attribute their high NEBM efficiency score to the high divisional efficiency score of h_s within the supply chain. The divisional efficiency scores of the NEBM model for partner S010 within supply chain N043, partner S088 within supply chain N0245, and partner S081 within supply chain N0281 are all 1. However, these partners are evaluated as inefficient DMUs in the CCR model. The CCR efficiency scores are 0.1827 for S010, 0.1507 for S081, and 0.1263 for S088, which are all below the median value (0.2387).

Unlike the NSBM and NEBM models with 0 efficient supply chains, 92 of the 540 supply chains record the NCCR efficiency score of 1. This is because a radial model has a lower discriminatory power than a non-radial model [46]. As described earlier, the ϵ_y^h of some divisions has a positive value because of the dispersion of the output. The overall efficiency score of the NEBM model is between the overall efficiency scores of the NSBM and NCCR models ($\rho_{NSBM}^* \le \gamma_{NEBM}^* \le \theta_{NCCR}^*$); the divisional efficiency score of the NEBM model is also between the divisional efficiency scores of the NSBM and NCCR models ($\rho_{NSBM}^{\mathrm{h}^*} \le \gamma_{NEBM}^{\mathrm{h}^*} \le \theta_{NCCR}^{\mathrm{h}^*}$). Meanwhile, in 81 h_ss and one h_p, the divisional efficiency scores of the NEBM and NCCR models are the same. This suggests that the ϵ_y^h of these divisions is 0. As such, the NEBM model is sensitive to the dispersion of data; it evaluates the DMUs using both radial and non-radial properties [29].

Table 5. Descriptive statistics of the CCR, network SBM (NSBM), network EBM (NEBM), and network CCR (NCCR) efficiency scores.

Efficiency Score	CCR	NSBM	NEBM	NCCR
Average	0.30110	0.07224	0.09241	0.96253
Median	0.23869	0.03322	0.04605	0.98801
St. dev.	0.18046	0.12517	0.14512	0.03683
Max	1.0000	0.95424	0.98657	1.0000
Min	0.05976	0.00037	0.00041	0.90500
The number of efficient DMU	2	0	0	91

Table 6. Descriptive statistics of the h_s divisional efficiency scores of the NSBM, NEBM, and NCCR models.

Efficiency Score	NSBM	NEBM	NCCR
Average	0.04592	0.05819	0.05901
Median	0.01693	0.02358	0.02421
St. dev.	0.11714	0.12732	0.12812
Max	1.0000	1.0000	1.0000
Min	0.00019	0.00020	0.00021
The number of efficient DMU	6	6	6

5. Determinant Factors of Automobile Supply Chain Efficiency

The Hyundai Motor Company promotes quality management through win–win cooperation with its partners. It provides both financial support (raising the unit prices of components from suppliers and paying for their labor costs) as well as non-financial support (R&D investment and quality control in manufacturing process) to enhance its partners' competitiveness and to ensure the supply of quality components. This ultimately enhances the quality competitiveness of its finished automobiles.

As the partnership with the Hyundai Motor Company strengthens, the unit prices the partner receive increase compared to the raw material cost. Thus, this allows the partner to benefit from high rates of return and enhanced efficiency. However, this leads to an increase in the price of finished automobiles and inefficiency in the overall supply chain [10]. When a supply contract that stipulates the unit price, quantity, quality standard, and other elements of automobile components concludes, the partners improve efficiency by minimizing costs at the estimated returns. However, from a total supply chain perspective, it is efficient to maximize the expected revenue by producing the maximum amount of high quality products at prepaid costs. The components produced by partners are intermediate products that are used as inputs for the next production processes; therefore, their quality affects the performance and durability of the finished automobiles. If partners compromise the quality of their products to reduce costs, efficiency may increase at an individual company level, but it would decrease at an overall supply chain level. In this context, the following hypothesis is established.

Hypothesis. *The partner efficiency has a negative impact on the overall supply chain efficiency.*

5.1. Mann–Whitney U Test

As the DEA method is a non-parametric method in which the efficiency score does not comply with normal distribution, Golany [47] suggested applying the Mann–Whitney U test to the DEA results. The Mann–Whitney U test is thus conducted to verify the existence of any significant statistical difference between the two groups divided in accordance with the aforementioned hypothesis. The results in Table 7 reveal that the NEBM efficiency score is lower in the supply chain with partners that have a CCR efficiency score of 1 than in the supply chain without such partners, at a significance level of 0.05.

Table 7. Mann–Whitney U test.

Variable		Mann–Whitney U	
	Mean	**Z Ratio**	***p*-Value**
Involved CCR efficient partners	0.01214	3.457	0.001 **
Not involved	0.09393		

Note: ** statistically significant at the 0.05 level.

5.2. Tobit Regression Model

Section 5.1 confirmed the difference in efficiency between supply chain groups with and without efficient partners. Therefore, we must clearly identify the cause of this difference. Many studies have used a regression analysis to examine the variables that affect the DEA efficiency scores [48]. However, as the DEA efficiency score (a dependent variable) is limited to a value between 0 and 1, and both sides exhibit truncated distribution, the ordinary least squares model obtains biased and inconsistent estimations [49]. The Tobit regression model is thus suggested to prevent this problem. It is used when the dependent variables are bounded from below, above, or both [50]. The following equation illustrates this model:

$$y_i^* = \beta x_i + \varepsilon_i,\quad y_i = \begin{cases} y_i^* \ if \ 0 \le y_i^* \le 1 \\ 0 \ if \ y_i^* < 0 \\ 1 \ if \ y_i^* > 1 \end{cases} \tag{5}$$

where y_i is the DEA efficiency score; y_i^* is a latent variable and x_i is a vector of explanatory variables; β is a vector of estimated parameters and ε_i refers to independent and identically distributed error terms with zero mean and variance σ^2.

We now estimate β and σ, which maximize the likelihood function L based on observations. Hence,

$$\mathrm{L} = \prod_{0<y_i<1} P(y_i|0 < y_i < 1) \prod_{y_i=0} P(y_i = 0) \prod_{y_i=1} P(y_i = 1) \tag{6}$$

where

$$P(y_i|0 < y_i < 1) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(y_i-\beta x_i)^2}{2\sigma^2}};$$

$$P(y_i = 0) = \frac{1}{\sqrt{2\pi\sigma^2}} \int_{-\infty}^{-\beta x_i} e^{-\frac{t^2}{2\sigma^2}} dt;$$

$$P(y_i = 1) = \frac{1}{\sqrt{2\pi\sigma^2}} \int_{-\infty}^{-(1-\beta x_i)} e^{-\frac{t^2}{2\sigma^2}} dt$$

In the Tobit regression analysis, the CCR efficiency score is an independent variable and the NEBM efficiency score is a dependent variable. The results are consistent with those of the Mann–Whitney U test. As Table 8 indicates, the CCR efficiency of the partners has a negative impact on the NEBM efficiency of the supply chain. In other words, the efficiency of the partners within the supply chain reduces the efficiency of the supply chain.

Table 8. Tobit regression model result.

Variable	Coefficient	Standard Error	Z	*p*-Value
Const.	0.153	0.012	12.815	0.000
CCRI	−0.201	0.034	−5.885	0.000 **
Log(scale)	1.718	0.310	5.536	0.000 **

Note: ** statistically significant at the 0.05 level.

6. Conclusions

The main purpose of this study was to identify the impact of the partner efficiency on the overall supply chain efficiency. Under the assumption that an automobile components supply contract has concluded, and the unit price, quantity, and quality standard are set, an input-oriented CCR model was used to measure the efficiency of the individual partners, while an output-oriented NEBM model was used to measure the efficiency of the overall supply chain. Then, the relationship between the efficiency of the partners and the entire supply chain was analyzed using the Mann–Whitney U test and the Tobit regression model.

In the first phase, two types of DEA models were used. The CCR model was applied to assess the competitiveness of the individual partners. The inputs comprised the number of employees, operating cost, and fixed assets, while and the output was the total gross sales. According to the results, only two of the 139 partners were identified as efficient DMU. The CCR efficiency scores are low in general, and 63% of all partners (88 of 139) have an efficiency score below the average. The NEBM model was applied to a three-tier supply chain comprising partners, subsidiaries, and parent companies. The inputs and outputs of the partners (non-affiliates of the Hyundai Motor Company) were selected based on the vendor selection criteria. The input of the partners was price, whereas the outputs were quality and delivery performance. The inputs of the subsidiary and parent companies were the number of employees and operating cost, while the outputs were the total gross sales and export sales. The intermediate product was material flow. The result of the NEBM model reveals that none of the 540 supply chains was located at the efficient frontiers. As only the supply chains with all divisions being efficient have an efficiency value of 1 in the NEBM model, the model has higher discriminatory power than the NCCR model. In addition, the NEBM model was suitable for measuring the efficiency of a complex supply chain as its similarity to the NSBM or NCCR models increased according to the dispersion of data. It evaluated efficiency considering both radial and non-radial properties.

Under a circumstance in which the unit price, quantity, quality standard, and delivery date are set, we suppose that partners would maintain quality only to the minimum requirement to minimize the production costs of components. However, as the quality of components corresponds to the output of the supply chain, a hypothesis was established—a partner's efficiency at cost reduction would have a negative impact on the overall supply chain efficiency. This hypothesis was verified through non-parametric and parametric methods.

In the second phase, a Mann–Whitney U test and a Tobit regression model were used. Two groups were created: a supply chain with partners indicating a CCR efficiency score of 1 and a supply chain without such partners. Then, the Mann–Whitney U test was conducted to verify the difference in the distribution of the NEBM efficiency scores between the two groups. The Tobit regression analysis was also conducted to identify the causal relationship between the CCR efficiency score and the NEBM efficiency score. The supply chain comprising the partners with a CCR efficiency score of 1 was less efficient than the supply chain without such partners. That is, the more efficient the partner, the less efficient the total supply chain would be.

This finding implied a conflict of interests within a supply chain consisting of independent companies and therefore supported similar studies reporting the lower performance of a supply chain under non-cooperative assumption [10,26]. Moreover, the quality score of efficient partners was not higher than that of inefficient partners, which is consistent with previous studies demonstrating that efficient suppliers focus on cost reduction, not on quality improvement [24].

In contrast to the results reported here, a previous study claimed that automakers' financial and technical support to partners would reduce supply chain inefficiency [14]. This discrepancy could be explained by differences in the industry environment. In the Indian automobile industry, manual labor was a poor substitute for automated equipment, while manufacturing processes in the Korean automobile industry were mostly automated to eliminate such inefficiencies.

The Hyundai Motor Group has increasingly pursued win–win cooperation with its partners because of political pressure and labor-management conflicts. Thus, its business strategy aims to increase its partners' competitiveness and ultimately enhance the quality competitiveness of its finished automobiles. However, as our study reveals, the efficient operations of the partners impair the efficiency of the total supply chain. This suggests that the effects of quality improvement on the partners are lower than the support provided by the Hyundai Motor Group. Considering our findings, the automobile industry must review its partner management system (evaluation criteria and incentive system) to establish a truly efficient supply chain. From a managerial point of view, this could give managers a deeper insight on designing and implementing supply chain integration. This approach also leads policymakers to a more realistic assessment for developing evaluation criteria in the automobile industry.

Even though this study utilized sharper efficiency estimates of a three-tier supply chain by applying the NEBM model, it has some limitations. In evaluating suppliers within the supply chain, a wider criterion can be adopted, while we only examined the core key indices because of limited data. This would include intangible elements such as information sharing, technological innovation, and partnership, aside from price, quality, and delivery performance. In addition, potential risks always exist in supply chain management, involving the risk in demand, production and logistics, and such risks may lead to data uncertainty. Thus, in future studies, methods such as fuzzy model can be used to deal with uncertainty and establish an efficient supply chain.

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