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A SCOR-Based Two-Stage Network Range-Adjusted Measure Data Envelopment Analysis Approach for Evaluating Sustainable Supply Chain Efficiency: Evidence from the Korean Automotive Parts Industry

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Abstract

This study evaluates the economic dimension of sustainable supply chain efficiency among Korean automotive suppliers using an SCOR-aligned two-stage Network Range-Adjusted Measure (NRAM) Data Envelopment Analysis (DEA) model. The framework separates performance into Stage 1 (internal operations: Plan/Source/Make/Deliver) and Stage 2 (external outcomes: sales and profitability), enabling stage-specific assessment of operational versus market-facing efficiency. Firm-level financial data for about 1200 suppliers annually from 2021 to 2024, spanning five sectors, were analyzed with descriptive statistics, visualizations, and non-parametric tests. Results show that Stage 1 efficiency was consistently high and stable, while Stage 2 efficiency was lower, more variable, and declined in 2022 and 2024, revealing vulnerability to systemic market disruptions. Overall efficiency mirrored Stage 2, underscoring the fact that downstream financial outcomes drive total performance. Rather than introducing a new methodology, the contribution of this study lies in applying an established two-stage NRAM DEA within an SCOR-aligned framework to a large-scale longitudinal dataset. This application provides sectoral and temporal benchmarks on a national scale, offering evidence-based insights into how structural interdependence and systemic shocks influence supply chain efficiency. While the scope is limited to the economic pillar of sustainability, the findings contribute contextualized benchmarks that can inform managerial practice and future research integrating environmental and social performance dimensions.

Keywords: network DEA; SCOR model; sustainable supply chain; automotive industry; two-stage efficiency; supply chain performance; range-adjusted measure of inefficiency

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1. Introduction

1.1. Background and Motivation

Sustainable supply chain performance has become a critical focus in the automotive industry as companies strive to remain competitive while also meeting economic, environmental, and social objectives [1,2]. In particular, the Korean automotive industry features a complex network of parts suppliers that play a pivotal role in overall industry efficiency and sustainability [3,4]. However, this industry faces persistent challenges, including heightened market volatility, global demand fluctuations, and supply chain fragility as revealed by the recent semiconductor shortage. These pressures highlight the urgent need

for resilience-oriented evaluation frameworks that can diagnose both operational and market-facing vulnerabilities. Traditional performance frameworks, which often assess metrics in isolation, are insufficient to capture such systemic risks. This motivates the use of an integrated two-stage efficiency evaluation framework, aligned with standardized supply chain process metrics and supported by an advanced benchmarking approach.

Measuring how efficiently these suppliers operate—and how their operations contribute to broader supply chain outcomes—is essential for identifying performance gaps and opportunities for improvement. However, traditional supply chain performance frameworks have limitations in this regard. For example, the Supply Chain Operations Reference (SCOR) model provides a comprehensive set of metrics covering cost, asset management, reliability, and other dimensions, but it evaluates each metric in isolation [5]. This siloed approach makes it difficult to capture an integrated view of how well a firm converts its resources into desired outcomes across the entire supply chain. There is a clear need for a holistic evaluation method that can overcome the limitations of single-metric and single-stage assessments, especially given the multifaceted nature of sustainability goals in supply chains.

Data Envelopment Analysis (DEA) offers a powerful approach to address this need by evaluating multiple inputs and outputs simultaneously to determine relative efficiency. DEA has been widely applied to measure organizational performance across various domains, including sustainable supply chain management, because it can handle multiple criteria in a single efficiency score [6]. Most prior DEA-based supply chain studies, however, treat the supply chain as a "black box" or single-stage process, which is a notable limitation [7]. By focusing only on one aggregated stage, traditional DEA applications may overlook inefficiencies or trade-offs occurring within sub-stages of the supply chain. In reality, supply chains consist of sequential stages—such as procurement/manufacturing and distribution/market delivery—each with its own inputs and outputs. To capture this internal structure, network DEA has been developed to decompose an organization's process into interconnected sub-processes [8]. A network DEA model not only evaluates overall efficiency but also assesses the efficiency of each stage, using intermediate outputs from the first stage as inputs to the second stage. This capability is highly relevant for supply chain analysis, as it mirrors the actual flow of materials and value, e.g., efficient internal operations (stage 1) should translate into strong market performance (stage 2). By adopting network DEA models, we can thus address the limitation of single-stage methods and gain deeper insight into where inefficiencies occur within the supply chain.

In this study, we leverage a two-stage network DEA approach to measure the sustainable supply chain efficiency of automotive parts suppliers in Korea. Our two-stage model is carefully aligned with the SCOR framework to reflect the distinct phases of supply chain activity. The first stage represents the internal-focused processes (Plan/Source/Make/Deliver in SCOR), essentially capturing operational efficiency in terms of resource usage and internal value creation. The second stage represents outward-focused processes, capturing how those internal efforts translate into market outcomes like sales and profitability [9,10]. By mapping the network DEA stages to SCOR components, we ensure that the efficiency evaluation covers the end-to-end supply chain: from internal operations to final value delivery. This integrated modeling is useful in that it bridges a well-established industry framework (SCOR) with an advanced efficiency analysis technique (network DEA), providing a more nuanced assessment of sustainable supply chain performance than previously possible. Unlike earlier similar SCOR–DEA applications, this study newly develops a Network Range-Adjusted Measure (NRAM) DEA model, which extends the conventional Range-Adjusted Measure (RAM) formulation [11] to a two-stage structure. Compared with

other network DEA variants, NRAM offers several distinctive advantages that are highly relevant in the context of Korean automotive suppliers, which are detailed in Section 2.1.

At the same time, we acknowledge that our model focuses on financial and operational variables (e.g., COGS, transportation costs, cash-to-cash cycle, revenue, and net income) due to data availability at scale. Environmental indicators such as carbon emissions and social indicators such as employee satisfaction are not included in the present dataset, which narrows the scope of "sustainable supply chain efficiency" primarily to its economic dimension. Nonetheless, we argue that this economic perspective remains valuable, as operational resilience in Stage 1 and market responsiveness in Stage 2 are foundational capabilities that indirectly support environmental and social sustainability—by enabling leaner operations, reducing waste and energy consumption, and ensuring more stable employment. This positioning highlights both the limitations of the current scope and the broader significance of our findings within the triple-bottom-line framework.

The contribution of this research is threefold. First, we advance methodology by developing a two-stage NRAM DEA model that captures stage-specific and overall inefficiencies while preserving desirable properties. Second, we apply this model to a large and unique dataset of approximately 1200 Korean automotive supplier firms annually from 2021 to 2024, disaggregated into five key sectors (Powertrain, Body, Trim, Electrical, and Chassis), to provide sectoral benchmarks. This extensive application not only demonstrates the model's capability but also yields practical benchmarks for different segments of the supplier network. Third, we conduct a longitudinal analysis over four years, using descriptive statistics, visualizations, and non-parametric tests to examine temporal dynamics in efficiency scores across both time and supplier sectors. This allows us to determine whether supply chain efficiency is significantly improving over time and to identify which types of supplier functions are excelling or lagging in performance. Our findings shed light on trends in sustainable supply chain efficiency: for instance, we can see whether industry-wide efficiency is on the rise and pinpoint functional areas that consistently outperform or underperform. These insights offer valuable guidance for managers seeking to target improvements and for policymakers aiming to support sustainable supply chain development in the automotive sector. This national-scale application provides incremental but valuable benchmarking evidence, highlighting how structural interdependence among suppliers and systemic shocks shape both internal and external efficiency. While the scope is limited to the economic pillar of sustainability, the results contribute to international sustainable supply chain management (SSCM) debates by offering robust context-specific insights and by setting a baseline for future extensions that integrate environmental and social indicators.

1.2. Literature Review

Performance measurement in supply chains has evolved from simple cost and productivity metrics to more holistic frameworks that incorporate multiple dimensions of performance and sustainability. The SCOR model, for example, defines metrics across reliability, responsiveness, agility, cost, and asset management for processes spanning plan, source, make, deliver, and return [12]. Researchers have highlighted that effective supply chain management and performance measurement are critical for sustainable competitive advantage [13–15]. In the context of automotive industries, early studies often focused on individual firm performance or buyer–supplier relationships, finding that collaboration and integration can improve overall supply chain outcomes [7,16]. However, purely qualitative or single-metric approaches fail to capture the multifaceted nature of supply chain efficiency and sustainability.

DEA has emerged as a prominent quantitative approach to evaluate supply chain performance due to its ability to handle multiple inputs and outputs without pre-assigned weights [7]. The traditional DEA "black-box" model treats the entire organization (or supply chain) as a single process, yielding an overall efficiency score. Pioneering work by Liang et al. [7] introduced DEA models tailored for supply chain efficiency evaluation, recognizing that a supply chain involves interrelated stages. Subsequently, network DEA models were developed to explicitly model such multi-stage structures. For instance, Färe and Grosskopf [16] first formulated the notion of network production systems in DEA. Kao [17] provides a comprehensive review of network DEA approaches, noting their applicability in cases where processes can be divided into sub-processes with intermediate products. Two-stage DEA models (a simple form of network DEA) have been widely applied: for example, in banking (front-office vs. back-office processes), education (teaching vs. research outputs), healthcare, and supply chains [18].

In supply chain applications, two-stage DEA allows efficiency to be assessed in, say, an upstream stage (e.g., procurement and production efficiency within a supplier) and a downstream stage (e.g., distribution and market efficiency of delivering value to customers). Chen and Yan [19] proposed a network DEA model for supply chain performance that linked suppliers and manufacturers, demonstrating the advantage of network DEA over separate evaluations. Tavana et al. [20] introduced a network epsilon-based measure (NEBM) DEA model to evaluate supply chain performance with multiple tiers. A later study by Tavana et al. [21] extended two-stage DEA to a three-level supply chain context (supplier–manufacturer–customer), highlighting how efficiency at different echelons can be aggregated. These studies underline that network DEA can identify stage-specific inefficiencies that would be hidden in aggregate models.

Beyond purely operational efficiency, the concept of sustainable supply chain performance has gained attention. This extends the evaluation to consider environmental and social performance alongside traditional economic efficiency. Izadikhah and Saen [22] specifically tackled sustainability in supply chains by using a two-stage Range Directional Measure (RDM) DEA that accommodated undesirable outputs (e.g., emissions). Their model evaluated how efficiently supply chains convert resources into both desirable outputs (service levels, profits) and reduced undesirable outputs, illustrating DEA's flexibility in sustainability assessment. Building on this, Izadikhah and Saen [23] extended the approach to a chance-constrained two-stage DEA model, allowing for the assessment of sustainability under uncertainty while still accounting for undesirable outputs. Other researchers have incorporated stochastic or fuzzy extensions to handle uncertainty in sustainable supply chain data. While our study does not explicitly include environmental metrics (focusing on financial and operational measures), the emphasis on efficiency and lean operations has clear sustainability implications. For example, reducing the cash-to-cash cycle or increasing asset turnover can lower waste and resource consumption, contributing to environmental sustainability indirectly.

In the automotive sector, supplier efficiency and its impact on the broader supply chain have been studied in various contexts. Saranga [24] analyzed the operational efficiency of Indian auto component manufacturers using DEA and found significant disparities in performance drivers. More recently, Kim and Kim [4] evaluated the Korean automobile supply chain by measuring the efficiency of 139 supplier firms (using a conventional DEA model) and the overall network efficiency of supply chain systems (using a network DEA model). Intriguingly, their results suggested that a supplier's high internal efficiency did not always translate into high supply chain efficiency for the OEM—in fact, efficient operation of some partners was found to hamper total supply chain efficiency. This highlights potential misalignments or trade-offs, where a firm optimizing its own costs and assets

might, for example, skimp on quality or flexibility, thereby negatively affecting downstream performance. Such findings motivate a deeper examination of stage-level efficiencies: it is important to understand whether being efficient in Stage 1 (operations) comes at the expense of Stage 2 (market outcomes) or vice versa.

Beyond DEA-specific studies, the broader SSCM literature emphasizes the integration of economic, environmental, and social performance dimensions (Carter and Rogers [1]; Seuring and Müller [2]). These frameworks highlight that sustainability cannot be reduced to financial metrics alone but requires coordination across triple-bottom-line objectives. Our study aligns with this perspective by explicitly focusing on the economic/financial dimension of supplier efficiency while acknowledging the importance of extending future analyses to environmental and social indicators.

While prior studies such as Liang et al. [7], Färe and Grosskopf [16], Chen and Yan [19], Tavana et al. [20,21], and Izadikhah and Saen [22,23] advanced methodological frontiers in network DEA, most were limited to cross-sectional or case-based datasets. Saranga [24] analyzed Indian automotive component firms and Kim and Kim [4] studied Korean suppliers, but both were constrained by relatively small samples and the absence of longitudinal scope. By contrast, our study applies a SCOR-aligned two-stage NRAM DEA to a four-year panel of 770–790 Korean suppliers annually, providing sectoral and temporal benchmarking of the financial dimension of sustainability at scale. Methodologically, this integration demonstrates the advantages of NRAM DEA—its ability to accommodate negative financial data, preserve unit invariance, orientation-free properties, and capture strong efficiency, making it a robust tool for benchmarking. Substantively, it contributes large-scale empirical evidence that complements and extends prior international research. A comparative summary of the scope, models, indicators, and limitations of related studies is presented in Table 1, which highlights how this study differs in terms of dataset scale, longitudinal coverage, and explicit SCOR alignment.

To summarize, the literature indicates that (1) two-stage/network DEA is a suitable approach for supply chain performance evaluation, providing insights into internal vs. external efficiency; (2) integrating multiple metrics, including those related to sustainability, is feasible in DEA, and (3) automotive supply chains present unique dynamics where internal efficiency and overall value creation must be balanced. Building on these insights, our study adopts a SCOR-based two-stage network DEA model with a non-radial efficiency measure (NRAM) to assess Korean automotive suppliers in different sectors. This approach fills a gap by linking established SCOR performance metrics with an advanced network DEA formulation, allowing us to gauge how well suppliers in different sectors convert resources into both operational excellence and financial results over time.

The remainder of this paper is structured as follows. Section 2 describes the research methodology, including the SCOR-based two-stage NRAM DEA framework, the dataset employed, and the details of the model formulation. Section 3 reports and discusses empirical findings, presenting efficiency score distributions, sectoral and temporal comparisons, and the results of statistical significance tests. Section 4 concludes the paper by summarizing the key findings, outlining their implications for the automotive supply chain, and suggesting directions for future research.

Table 1. Comparative Positioning of DEA-Based Studies on Supply Chain and Automotive Industries.

Study	Industry/Scope	Model Type	Stage Definitions	Indicators	Sample & Period	Notable Features	Limitations
Liang et al. [7]	Buyer–Seller supply chain (generic)	Network DEA (two-stage)	Buyer → Seller	Abstract variables: inputs (labor, capital, materials), intermediates (generic), outputs (final products, sales)	Numerical illustration (no large empirical dataset)	First DEA model tailored to buyer–seller SC efficiency	Abstract indicators; illustrative only
Färe and Grosskopf [16]	General production systems	Network DEA	Multi-stage production	Generic inputs, intermediates, value-added outputs	Conceptual/case-based	Foundational network DEA concept	Not SC-specific; no large empirical data
Chen and Yan [19]	Supply chains (SCs)	Network DEA	Supplier–Manufacturer linkage	Case-specific input/output sets (supplier resources; manufacturer performance)	Empirical example (case-based; limited size)	Shows advantage vs. separate evaluations	Limited scope; not large-scale
Tavana et al. [20]	Multi-tier SC	Network DEA (NEBM)	Supplier → Manufacturer → Distributor	Case-based: inputs (labor, capital, materials), intermediates (semi-finished goods), outputs (service, delivery, revenue)	Case-based validation	Introduced NEBM for SC performance	Mainly methodological; not a large panel
Tavana et al. [21]	Three-level SC	Network DEA (multi-echelon)	Supplier–Manufacturer–Customer	Tier-specific inputs/outputs across echelons	Cross-sectional, limited size	Multi-echelon benchmarking	No longitudinal panel
Izadikhah and Saen [22,23]	Sustainable SC	Two-stage DEA (RDM; chance-constrained)	Stage 1: operations; Stage 2: outcomes	Includes undesirable outputs (emissions/waste); uncertainty via chance constraints	Cross-sectional	Sustainability indicators; uncertainty handling	Not longitudinal
Saranga [24]	Indian automotive components	DEA (black-box)	Firm-level	Inputs (labor, capital, materials); outputs (sales, value added)	Cross-sectional sample of Indian firms	Heterogeneity in efficiency drivers	Regional scope; limited generalizability
Kim and Kim [4]	Korean automotive suppliers	DEA + Network DEA	Firm vs. SC system	Inputs (costs, assets, labor); outputs (sales, profit, ratios)	139 firms, single year	Korean case with network DEA	Small dataset; no time series; no sectoral comparison
This study	Korean automotive suppliers (5 sectors)	Two-stage NRAM DEA	Stage 1 = SCOR Plan/Source/Make/Deliver; Stage 2 = market outcomes	Stage 1 inputs (COGS, transport, C2C); intermediates (inventory & PPE turns); Stage 2 outputs (revenue, net income)	770–790/year, 2021–2024	Large-scale longitudinal panel; non-parametric tests; sectoral benchmarking	Economic dimension only (no env./social yet)

2. Materials and Methods

2.1. Network RAM DEA Model Formulation

To evaluate the efficiency of each supplier, we employ a two-stage network DEA model with RAM as the efficiency metric. The RAM, introduced by Cooper, Park, and Pastor [11], is a non-radial measure of inefficiency that accounts for input/output slacks normalized by the range of each variable. We extend RAM to the network case (two-stage DEA) by formulating a linear programming problem that simultaneously considers Stage 1 and Stage 2 performance for each Decision-Making Unit (DMU), subject to linking constraints for the intermediate measures. The model minimizes normalized input and output slacks across two stages, with linking constraints connecting Stage 1 outputs to Stage 2 inputs. This non-radial structure allows efficiency to be assessed at each stage and overall. This approach is referred to as the Network RAM (NRAM) DEA model, ensuring that inefficiencies in either stage contribute to the overall inefficiency score. The NRAM inherits several important and desirable properties of RAM, while being capable of dealing with a two-stage network setting.

First, it is non-radial, meaning that inefficiencies in each performance metric are measured individually rather than being forced to contract or expand proportionally. This is important because suppliers may show inefficiencies in cost control while performing well in asset utilization, and both should be captured separately. Second, it is orientation-free, allowing the model to evaluate inefficiency without assuming input minimization or output maximization in advance. This is crucial in supply chains where both cost reduction and revenue generation matter simultaneously. Third, it is unit-invariant, so variables measured in different units—such as costs, assets, and turnover ratios—can be compared in a single framework without distortion. Fourth, it can handle negative values [25], which is essential for financial data in this sector, where some firms report negative net income in certain years. Finally, it captures strong efficiency, ensuring that only suppliers with zero slacks in all dimensions are considered fully efficient, which provides a rigorous benchmark for best practices. By combining these properties, the SCOR-aligned two-stage NRAM DEA provides a robust and context-appropriate tool for sectoral and temporal benchmarking.

Mathematically, for each DMU k (where $k = 1, 2, \cdots, n$ suppliers in a given year), we solve the following linear program (under variable returns-to-scale assumptions for each stage):

$$\begin{aligned}
\min \quad & -\frac{1}{m+s}\left(\sum_{i=1}^{m}\frac{s_i^-}{R_i^-}+\sum_{r=1}^{s}\frac{s_r^+}{R_r^+}\right) \\
s.t. \quad & \sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = x_{ik}, \quad i = 1,\ 2,\ \cdots,\ m; \\
& \sum_{j=1}^{n} z_{dj}\lambda_j - \sum_{j=1}^{n} z_{dj}\mu_j \geq 0, \quad d = 1,\ 2,\ \cdots,\ D; \\
& \sum_{j=1}^{n} y_{rj}\mu_j - s_r^+ = y_{rk}, \quad r = 1,\ 2,\ \cdots,\ s; \\
& \sum_{j=1}^{n} \lambda_j = 1, \quad \sum_{j=1}^{n} \mu_j = 1; \\
& \lambda_j,\ \mu_j,\ s_i^-,\ s_r^+ \geq 0.
\end{aligned} \tag{1}$$

In this formulation, the two-stage structure is captured by two sets of intensity variables: λ_j (for Stage 1 reference combination) and μ_j (for Stage 2 reference combination) with j denoting the index of DMUs ($j = 1, 2, \cdots, n$). The indices are: i for Stage 1 inputs ($i = 1, 2, \cdots, m$), d for intermediate outputs ($d = 1, 2, \cdots, D$), and r for Stage 2 outputs ($r = 1, 2, \cdots, s$). The matrices $X = [x_{ij}]$, $Z = [z_{ij}]$, $Y = [y_{ij}]$ represent the data for all DMUs (inputs, intermediates, outputs). For DMU k, x_{ik}, z_{dk}, y_{rk} are its specific data.

The decision variables $s_i^- \geq 0$ and $s_r^+ \geq 0$ are slack (surplus) variables representing any inefficiency in inputs and outputs, respectively. The first constraint ensures that the reference (a convex combination of other DMUs via λ_j) uses no more of any input i than DMU k (input-oriented condition, allowing s_i^- if DMU k uses more input than needed to produce the reference output). The third constraint ensures the reference outputs (via μ_j combination) meet or exceed DMU k's outputs (output-oriented condition, with s_r^+ capturing shortfalls). The second constraint is the linking constraint: it requires that the amount of intermediate outputs generated by the Stage 1 reference (left side) is at least as large as the amount of intermediate inputs required by the Stage 2 reference (right side). This guarantees the feasibility of a two-stage production: Stage 1's composite can produce the necessary intermediates for Stage 2's composite. The λ and μ summation constraints (=1) impose variable returns-to-scale (VRS) on each stage's frontier (convexity constraint), which is appropriate here since we cannot assume constant returns in complex supply chain processes. All variables are non-negative, and we assume the intermediate products are freely transferable internally (no additional weight constraints on Z beyond the linking inequalities).

The objective function is the Range-Adjusted Measure of inefficiency for DMU k. It computes the weighted sum of all slacks (input excess and output shortfall) normalized by the range of each variable, and multiplies by $-\frac{1}{m+s}$ so that the objective is to maximize efficiency (or equivalently minimize inefficiency) and its value is bounded between -1 and 0. Here R_i^- is the range of input i across all DMUs ($\max_j x_{ij} - \min_j x_{ij}$) and R_r^+ is the range of output r ($\max_j y_{rj} - \min_j y_{rj}$). This normalization makes the slack units commensurate and bounded between 0 and 1 for each dimension. The optimal objective value will lie between -1 and 0, with 0 indicating that no slacks are present (the DMU lies on the efficient frontier in both stages). Values closer to 0 (less negative) indicate better performance, whereas more negative values mean larger slacks (inefficiency).

Once Model (1) with DMU k under evaluation is solved, we can derive the efficiency scores for Stage 1, Stage 2, and the overall score for DMU k following the RAM model definitions:

- Stage 1 efficiency: $e_{1k} = 1 - \frac{1}{m}\sum_{i=1}^{m} \frac{s_i^{-*}}{R_i^-}$, where s_i^{-*} are the optimal input slacks for DMU k. Essentially, this is 1 minus the average normalized input slack. If DMU k has no input excess ($s_i^{-*} = 0$ for all i), then $e_{1k} = 1$ (fully efficient in Stage 1). Any non-zero slack will reduce e_{1k} below 1.
- Stage 2 efficiency: $e_{2k} = 1 - \frac{1}{s}\sum_{r=1}^{s} \frac{s_r^{+*}}{R_i^+}$, using optimal output slacks. This is 1 minus the average normalized output shortfall. No shortfall ($s_r^{+*} = 0$ for all r) means $e_{2k} = 1$ (fully efficient in Stage 2). If a firm cannot attain the outputs achieved by any combination of peers (thus needing positive s_r^{+*}), e_{2k} will drop below 1.
- Overall efficiency: We take a weighted average of the two stages' scores (weighted by the proportion of the number of variables in each stage) as: $e_k = \frac{m}{m+s} e_{1k} + \frac{s}{m+s} e_{2k}$. Substituting the definitions of e_{1k} and e_{2k}, this simplifies to $e_k = 1 - \frac{1}{m+s}\left(\sum_{i=1}^{m} \frac{s_i^-}{R_i^-} + \sum_{r=1}^{s} \frac{s_r^+}{R_r^+}\right)$. Thus, the overall efficiency directly corresponds to the optimized objective value in Model (1). An overall $e_k = 1$ indicates the DMU is on the network efficiency frontier (no slack in any constraint, so it is best practice in both stages). Any value $e_k < 1$ indicates the proportion by which the DMU could, in theory, improve its outputs and/or reduce its inputs without hurting either stage's performance.

This NRAM DEA model is solved for each year separately. For each of the four years, we treated the set of firms as DMUs and solved n linear programs (one per firm) to obtain efficiency scores. The model is implemented in Python 3.10.9 using Gurobi 12.0.3, a state-of-the-art linear programming solver, to ensure computational efficiency.

2.2. Performance Variables

Following the SCOR framework, we select performance variables that capture cost efficiency, asset utilization, and overall financial performance in a two-stage network DEA model. Stage 1 represents internal supply chain operations (reflecting SCOR's Plan/Source/Make/Deliver processes), using inputs that cover key costs and working capital. Stage 2 represents the value outcomes (sales and profitability) achieved from those operations. The chosen variables are theoretically grounded in SCOR's Level 1 performance metrics—notably the cost and asset management efficiency attributes [5,26,27]—and have been employed in prior sustainable supply chain efficiency studies.

The selected variables focus on the economic dimension of sustainability. Stage-1 indicators (COGS, transportation costs, cash-to-cash cycle) capture resource efficiency and working capital management, while Stage-2 indicators (revenue and net income) reflect financial outcomes of market performance. This design emphasizes financial sustainability, consistent with the availability of standardized firm-level data. However, environmental and social performance indicators were not included due to data limitations. We acknowledge this scope as a limitation and note that integrating environmental and social metrics in future research would provide a more comprehensive triple-bottom-line perspective. Each variable is justified as follows:

2.2.1. Stage 1 Inputs (Operational Resource Expenditures)

- Cost of Goods Sold (COGS): COGS represents the direct production and sourcing costs for goods sold, reflecting how efficiently a supplier manages procurement and manufacturing expenses [26]. In SCOR terms, COGS is a component of total supply chain cost; minimizing COGS is crucial for cost efficiency. A lower COGS indicates leaner operations and less resource waste, which contributes to economic sustainability. Prior studies note that most supply chain costs reside in COGS, making it a fundamental indicator of supply chain efficiency [26]. Thus, COGS is included as a Stage 1 input to capture the cost dimension of sustainable supply chain management.
- Transportation Cost: This variable captures the logistics cost of delivering products, aligning with the SCOR Deliver process. Transportation cost is a major element of "cost to serve" in supply chains. Reducing transport expenses (e.g., via route optimization or load consolidation) improves overall supply chain cost efficiency. By including Transportation Cost as an input, we account for the efficiency of distribution activities—a key concern in sustainable supply chains, as efficient logistics not only cut costs but also reduce fuel usage and emissions [28,29]. It reflects the SCOR cost performance attribute by emphasizing the need to minimize total delivery-related process costs without sacrificing service.
- Cash-to-Cash Cycle Time: Cash-to-cash cycle time (measured in days) is a Level 1 SCOR metric for asset management efficiency [5,26,27]. It tracks the duration between paying for raw materials and receiving customer payment, encompassing inventory, receivables, and payables periods. We treat cash-to-cash time as an input (to be minimized) because a shorter cycle frees up working capital and indicates a more agile, financially sustainable supply chain [26]. A low cash-to-cash cycle implies the company quickly converts its expenditure into revenue, improving liquidity and reducing the capital tied up in operations. This is not only financially beneficial but also aligns with sustainability goals by reducing the buffer stock and storage needs. By including cash-to-cash time, our model captures the efficiency of working capital management, consistent with SCOR's asset management focus (e.g., SCOR AM1.1 cash-to-cash KPI).

In sum, the Stage 1 inputs (COGS, transport cost, and cash-to-cash days) represent the resource investments and capital requirements for running the supply chain, echoing SCOR's cost and asset metrics and providing a basis for measuring operational efficiency in a sustainable context.

2.2.2. Intermediate Measures (Stage 1 Outputs → Stage 2 Inputs)

- Inventory Turnover: Inventory turnover (inventory "turns" per year) is a classic supply chain efficiency KPI indicating how many times a firm sells and replaces its stock in a period. A higher turnover signifies that inventory is managed tightly—products move faster through the pipeline, and excess stock (waste) is minimized. This metric directly reflects lean supply chain practices [30]: frequent inventory turns mean the company operates with less idle stock, which is both cost-effective and reduces obsolescence and storage resource usage. The SCOR model highlights Inventory Days of Supply/Inventory Turns as key asset metrics [27], and notes that improving inventory turns shortens the cash-to-cash cycle [26]. Indeed, a faster inventory turnover means cash invested in inventory is recovered more quickly, improving liquidity. We include inventory turnover as the output of Stage 1 (and input to Stage 2) to indicate how effectively the Stage 1 inputs (costs and capital) are transformed into throughput. It captures internal operational performance in terms of inventory management efficiency—a critical aspect of sustainable supply chains, since lean inventories can reduce holding costs and environmental footprint (through lower warehousing and spoilage).
- Property, Plant & Equipment (PPE) Turnover: PPE turnover is defined as revenue generated per unit of fixed assets (annual sales ÷ net PPE, for example). This metric gauges how efficiently a firm utilizes its fixed assets—factories, machines, vehicles, etc.—to produce output. The automotive parts supplier industry is highly capital-intensive, so effective use of facilities and equipment is vital for both competitiveness and sustainability (idle capacity represents wasted capital and energy). SCOR's Level 1 asset metrics explicitly include Return on Supply Chain Fixed Assets [27], which measures profit or revenue relative to fixed assets invested. Our use of PPE turnover aligns with this concept of asset utilization: a higher PPE turnover indicates that the supplier is generating more output (sales) per dollar of asset investment, implying productive, efficient use of its capital infrastructure. By treating PPE turnover as an intermediate output of Stage 1, we capture the outcome of internal process efficiency in terms of asset usage [31]. Together with inventory turns, it represents the internal operational excellence (fast inventory cycle and high asset productivity) that forms the input to Stage 2. In other words, these intermediates are the capabilities developed in Stage 1 that will drive financial performance in Stage 2. This approach resonates with the Resource-Based View: efficient use of resources (short cash cycle, low costs, high asset turnover) builds operational capabilities, which then translate into better outcomes in the next stage.

2.2.3. Stage 2 Outputs (Final Performance Outcomes)

- Revenue: We use Revenue (annual sales) as one final output of Stage 2 to represent the market success of the supply chain. Revenue reflects how well the firm's upstream supply chain performance is translated into customer demand fulfillment and sales generation. In the SCOR framework, the culmination of Plan/Source/Make/Deliver processes is the delivery of a product to the customer; Revenue captures the monetary value of these delivered products. A higher revenue, given on the same operational base, indicates greater efficiency in responding to market needs and exploiting demand opportunities. Including Revenue allows the network DEA model to evaluate

each supplier's ability to convert operational efficiency into top-line performance. Notably, prior two-stage DEA studies often treat a "sales generation" stage separate from a "profit generation" stage to assess both market efficiency and cost management efficiency [17,31]. By explicitly considering Revenue, we acknowledge that a sustainable supply chain must not only run efficiently internally but also effectively drive sales in the marketplace.

- Net Income: Net Income (profit) is the second Stage 2 output, reflecting the bottom-line financial performance and profitability of the supply chain's operations. Profitability is a key aspect of the economic dimension of sustainability, ensuring the long-term viability of the supplier. Net Income effectively measures how efficiently the firm's supply chain operations and revenues are converted into earnings. By including both Revenue and Net Income, we distinguish between efficiency in generating sales and efficiency in controlling costs to yield profit [31]. This distinction has theoretical and empirical support: for example, some network DEA studies evaluate the first stage that produces revenue and the second stage that yields profit from that revenue. In our context, a high revenue coupled with a modest profit would signal issues in cost management or value addition, whereas strong performance in both indicates a truly efficient and sustainable supply chain. Thus, Net Income serves as a comprehensive outcome metric, encapsulating the impacts of cost efficiency, asset utilization, and market performance on the firm's financial health. It aligns with SCOR's emphasis on value (Return on Assets and Return on Working Capital ultimately manifest in profit) and has been used in prior sustainable DEA models as an ultimate performance indicator.

In summary, the selected variables align with SCOR Level 1 performance metrics and pillars of supply chain performance. The Stage 1 inputs (COGS, transportation cost, cash-to-cash time) capture the cost and capital investment required in the supply chain, consistent with SCOR's cost and asset management attributes. The intermediate measures (inventory and PPE turnover) reflect operational efficiency and asset productivity, paralleling SCOR metrics like inventory turns and return on fixed assets. Finally, the Stage 2 outputs (revenue and net income) represent the value creation and financial sustainability resulting from the supply chain, separating the revenue-generating capability from profit efficiency as recommended in the literature. This SCOR-grounded selection of variables is well-supported by previous studies in two-stage and sustainable DEA contexts—for instance, Izadikhah and Saen [23] employ a two-stage DEA to evaluate sustainable supply chain performance with similar economic metrics—and is particularly appropriate for the Korean automotive supplier industry, where controlling costs, turning inventory rapidly, fully utilizing expensive production assets, and ultimately translating operational excellence into sales and profits are all critical for competitive and sustainable supply chain management. The use of these variables ensures our network DEA model is firmly rooted in established supply chain performance theory (SCOR) and empirical practice, capturing a holistic picture of sustainable supply chain efficiency from operational inputs to financial outcomes.

2.3. Data Source and Preprocessing

Firm-level financial data for the Korean automotive parts industry, spanning 2021 to 2024, were obtained from the "Value Search" service provided by NICE Information Service Co., Ltd., Seoul, Republic of Korea [32], a nationally well-recognized provider of corporate financial disclosures. This database covers the majority of registered firms in the Korean automotive parts sector, including Tier-1 and Tier-2 suppliers, ensuring that both large and mid-sized firms are represented. While some very small private firms may be underrepresented, the coverage of major suppliers relevant to industry-wide performance

is comprehensive. The dataset includes seven core variables aligned with the SCOR-based two-stage NRAM DEA framework—comprising inputs, intermediate outputs, and final outputs—as detailed in a previous section.

To enhance the validity of efficiency estimation, we first applied a standardized two-step preprocessing procedure across all four years. First, outliers were identified and removed using the interquartile range (IQR) method, with observations lying beyond $\pm 3 \times$ IQR excluded to mitigate the influence of extreme values often present in financial data. This threshold was chosen because it is more conservative than the commonly used $\pm 1.5 \times$ IQR, thereby minimizing the risk of excluding valid but extreme-performing firms, while still reducing the undue influence of statistical outliers on efficiency scores. For transparency, we report that this procedure excluded approximately 33% of firms each year (2021: 379 firms removed out of 1155, final N = 776; 2022: 385 firms removed out of 1152, final N = 767; 2023: 392 firms removed out of 1168, final N = 776; 2024: 392 firms removed out of 1183, final N = 791), with the resulting samples still exceeding 750 firms annually. This demonstrates that the overall representativeness of the dataset remains intact after preprocessing.

Second, robust scaling was performed for all variables using the median and IQR, rather than the mean and standard deviation, in order to reduce the effect of skewed distributions and improve numerical stability during model computation.

Importantly, because the NRAM DEA model possesses translation invariance—a mathematical property that ensures efficiency scores remain unchanged under linear transformation of input and output data—the robust scaling step, although applied for computational robustness, does not alter the final efficiency results. This property allows us to safely scale the data without distorting the network DEA frontier or biasing inter-temporal comparisons. Furthermore, as some financial variables in our dataset (e.g., net income) include negative values, the translation invariance of the NRAM DEA model also ensures that such negative data can be incorporated directly, without the need for arbitrary transformation or exclusion. This enables a more faithful representation of firm-level financial performance, particularly when evaluating supply chain sustainability over multiple years. The consistent application of this preprocessing procedure across years supports both cross-sectional benchmarking and time-series analysis of sustainable supply chain efficiency.

DEA estimates are obtained under a finite sample and, in principle, may be affected by finite-sample (inward-frontier) bias. Bootstrap bias-correction and confidence intervals have been advocated primarily when the number of DMUs is limited relative to model dimensionality. In our application, the sample is large (~770 DMUs) compared to the number of inputs, intermediates, and outputs (3, 2, and 2), so the classic finite-sample bias is expected to be modest. Moreover, established bootstrap procedures for general two-stage/network DEA and, in particular, for stage-specific efficiency while preserving linking constraints, are not yet standardized. We therefore report deterministic estimates and treat bootstrap inference as a potential extension.

3. Results

3.1. Descriptive Statistics

Using the two-stage NRAM DEA model, we computed efficiency scores for each of the four years 2021–2024, evaluating Stage 1 (internal operations) and Stage 2 (external outcomes) efficiency for roughly 767–791 automotive suppliers (from an original dataset of about 1200 suppliers, after removing outlier cases) per year. Table 2 presents the descriptive statistics of the efficiency scores (Stage 1, Stage 2, and Overall efficiency) for each year. Each cell shows the Mean, Median, Standard Deviation (Std), Minimum, and Maximum of efficiency scores in that year for the given efficiency measure. Stage 1 Efficiency corre-

sponds to internal operations efficiency (Plan/Source/Make/Deliver), Stage 2 Efficiency corresponds to external outcome efficiency (sales and profitability), and Overall Efficiency is the two-stage network DEA efficiency.

Table 2. Descriptive statistics of supplier efficiency scores by year (2021–2024).

Year	Efficiency Type	Mean	Median	Std	Min	Max
2021 (N = 776)	Stage 1 Efficiency	0.826	0.851	0.120	0.370	1.000
	Stage 2 Efficiency	0.475	0.437	0.140	0.181	1.000
	Overall Efficiency	0.686	0.693	0.064	0.462	1.000
2022 (N = 767)	Stage 1 Efficiency	0.842	0.870	0.107	0.383	1.000
	Stage 2 Efficiency	0.395	0.361	0.117	0.095	1.000
	Overall Efficiency	0.663	0.663	0.057	0.438	1.000
2023 (N = 776)	Stage 1 Efficiency	0.830	0.858	0.114	0.296	1.000
	Stage 2 Efficiency	0.459	0.426	0.128	0.155	1.000
	Overall Efficiency	0.682	0.682	0.055	0.453	1.000
2024 (N = 791)	Stage 1 Efficiency	0.839	0.872	0.106	0.289	1.000
	Stage 2 Efficiency	0.383	0.340	0.121	0.065	1.000
	Overall Efficiency	0.657	0.657	0.072	0.362	1.000

Stage 1 (internal) efficiency scores were consistently much higher than Stage 2 (external) scores in every year, with Stage 1 also showing less variability across firms. For example, in 2021, the average internal efficiency was 0.826 versus only 0.475 for external efficiency, and even by 2024, this gap persisted (Stage 1 mean 0.839 vs. Stage 2 mean 0.383). The median values mirror this disparity (median Stage 1 $\approx$ 0.85–0.87 each year, versus median Stage 2 $\approx$ 0.34–0.44). Stage 1 scores also varied less across firms (std 0.10–0.12) than Stage 2 (std 0.13–0.15), indicating greater consistency in internal process efficiency across suppliers, whereas external outcome efficiency was more widely dispersed. As expected, the overall efficiency values fell in between the two stages (mean 0.66–0.69, std 0.05–0.07), since they aggregate the performance of both stages. This suggests that the drop in total efficiency was driven primarily by external factors and Stage 2 performance issues around 2022 and again in 2024. Figure 1 illustrates these patterns, showing that Stage 1 efficiency distributions are consistently high with narrow interquartile ranges across all years, while Stage 2 efficiencies are markedly lower and more dispersed, with numerous low outliers, particularly in 2022 and 2024. Overall efficiency falls between the two stages, reflecting the combined effect of strong internal operations and more variable external outcomes.

All years saw at least one firm achieve full efficiency (1.000) in each stage and overall, while the least efficient firms—especially in Stage 2—scored very low. Notably, by 2024, the minimum Stage 2 efficiency had dropped to an extremely low 0.065 (down from 0.181 in 2021), and the lowest overall efficiency fell to 0.362 (vs. around 0.45 in earlier years). This suggests the emergence of some highly underperforming suppliers in the later years. We also observe slight temporal shifts in performance: Stage 2 efficiency deteriorated over time (mean declining from 0.475 in 2021 to 0.383 in 2024), which contributed to a slight dip in overall mean efficiency by 2024 (0.657, down from 0.686 in 2021). In contrast, Stage 1 efficiency remained high and stable around 0.83–0.84 each year (with a minor uptick in 2022 and 2024). The statistical significance of these trends is analyzed in the time-series section below.

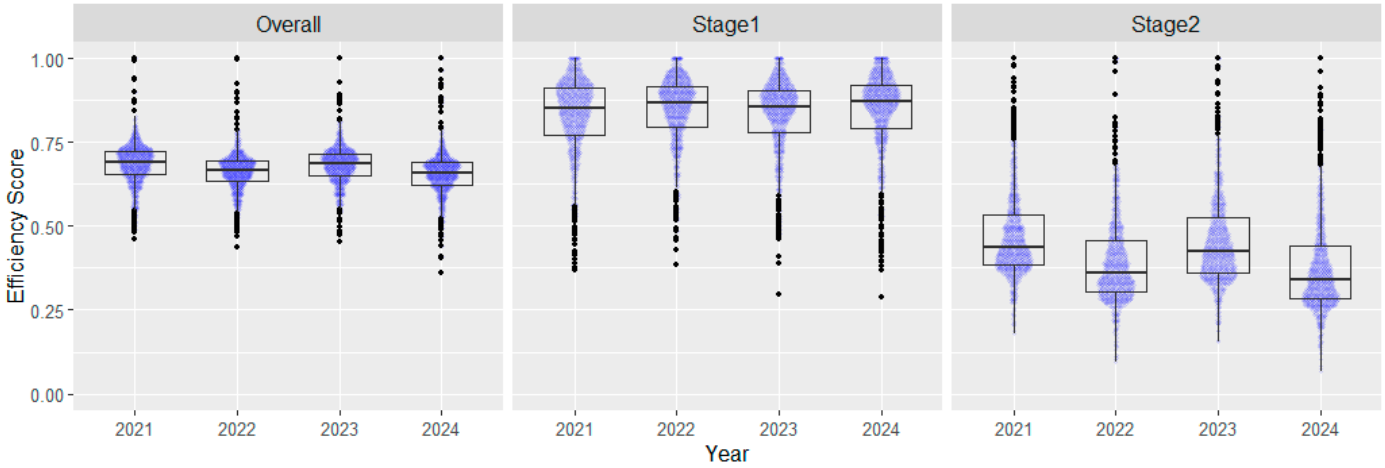


Figure 1. Box Plot Visualization of DEA Efficiency Scores (Overall, Stage 1, Stage 2). The box represents the interquartile range (IQR) from the first quartile (Q1) to the third quartile (Q3), with the central line indicating the median. The whiskers extend to the minimum and maximum values within 1.5×IQR, while black dots denote outliers beyond this range. Blue points represent individual efficiency scores displayed as a swarm plot to illustrate the distribution of observations. Each facet corresponds to a different efficiency metric (Overall, Stage 1, and Stage 2).

3.2. Sectoral Efficiency Comparison

To investigate performance differences among supplier sectors, we analyzed efficiency scores by sector (Powertrain, Body, Chassis, Trim, and Electrical) for each stage and year. Tables 3–5 present the median efficiency in each sector for Stage 1, Stage 2, and Overall efficiency, respectively, from 2021 through 2024. These results enable a comparison of internal vs. external efficiency across different functional supplier groups, as well as how each sector's performance evolved year-to-year.

Table 3. Stage 1 (Internal Operations) Median Efficiency by Sector (2021–2024).

Sector	2021	2022	2023	2024
Body	0.839 (N = 109)	0.863 (N = 99)	0.849 (N = 96)	0.872 (N = 97)
Chassis	0.824 (N = 34)	0.826 (N = 34)	0.821 (N = 35)	0.848 (N = 37)
Electrical	0.847 (N = 91)	0.865 (N = 93)	0.854 (N = 93)	0.874 (N = 91)
Powertrain	0.832 (N = 108)	0.85 (N = 105)	0.846 (N = 112)	0.864 (N = 117)
Trim	0.859 (N = 434)	0.876 (N = 436)	0.867 (N = 440)	0.875 (N = 449)

Table 4. Stage 2 (External Outcomes) Median Efficiency by Sector (2021–2024).

Sector	2021	2022	2023	2024
Body	0.436 (N = 109)	0.357 (N = 99)	0.416 (N = 96)	0.35 (N = 97)
Chassis	0.455 (N = 34)	0.365 (N = 34)	0.425 (N = 35)	0.369 (N = 37)
Electrical	0.458 (N = 91)	0.366 (N = 93)	0.436 (N = 93)	0.341 (N = 91)
Powertrain	0.465 (N = 108)	0.387 (N = 105)	0.442 (N = 112)	0.357 (N = 117)
Trim	0.429 (N = 434)	0.354 (N = 436)	0.419 (N = 440)	0.333 (N = 449)

Table 5. Overall Network Median Efficiency by Sector (2021–2024).

Sector	2021	2022	2023	2024
Body	0.685 (N = 109)	0.661 (N = 99)	0.673 (N = 96)	0.656 (N = 97)
Chassis	0.698 (N = 34)	0.676 (N = 34)	0.686 (N = 35)	0.672 (N = 37)
Electrical	0.699 (N = 91)	0.671 (N = 93)	0.684 (N = 93)	0.662 (N = 91)
Powertrain	0.684 (N = 108)	0.663 (N = 105)	0.678 (N = 112)	0.647 (N = 117)
Trim	0.694 (N = 434)	0.668 (N = 436)	0.691 (N = 440)	0.662 (N = 449)

Looking first at Stage 1 (Table 3), all sectors achieved very high internal operations efficiency, and the differences between sectors are relatively minor. Over the four years, the median Stage 1 efficiencies for each sector are clustered between approximately 0.82 and 0.88. For example, in 2024, the highest median Stage 1 efficiency is in the Body sector (0.872) and the lowest is in Chassis (0.848), a gap of only 0.024. Trim and Electrical suppliers also consistently exhibit top-tier internal efficiency, while Powertrain and Chassis suppliers tend to be slightly lower on this metric. These results indicate that all categories of suppliers have strong and nearly uniform internal process efficiency—a reflection of widespread adoption of lean operations and best practices within the industry's plants. Any sector-to-sector variations in Stage 1 are very slight; for instance, Powertrain suppliers showed a slightly lower median in 2021 (0.832) but had caught up by 2024 (0.864). Overall, there is no pronounced leader or laggard in internal efficiency, as every sector's median Stage 1 score lies near the efficiency frontier.

Stage 2 efficiency (Table 4) is much lower on an absolute scale and shows more noticeable differences across sectors. In all years, Powertrain suppliers demonstrate relatively higher external outcome efficiency than other sectors—for example, Powertrain's Stage 2 median was the highest in 2021 (0.465) and remained the highest in 2023 (0.442). The Electrical and Chassis sectors generally form the next tier, with intermediate Stage 2 performance. Trim suppliers consistently rank at the bottom in external efficiency; their Stage 2 median in 2024 was only 0.333, significantly below the medians of other sectors (which ranged from 0.35 to 0.37). This pattern (Powertrain > Electrical/Chassis > Body > Trim) is observed in most years, although there are minor exceptions. In 2023, for instance, the Chassis sector temporarily achieved the highest Stage 2 median (0.425)—slightly above Powertrain's 0.442—suggesting a strong external performance for Chassis suppliers that year. By 2024, however, Chassis had fallen back toward the sector average. In general, the gaps between sectors' Stage 2 medians are on the order of 0.02–0.04, which, while not large, are meaningful given the low absolute values. The greater spread and variability in Stage 2 implies that external market-facing performance is more uneven and dependent on sector-specific factors. Notably, Trim suppliers, despite their excellent internal efficiencies, struggle to convert those into external success—a point that may indicate structural challenges for trim/interior suppliers in the market or possibly a trade-off between internal focus and external flexibility.

When considering overall network efficiency (Table 5), the differences among sectors largely disappear. In each year, the median overall efficiency for every sector falls within a very tight range. For example, in 2021, the medians ranged from 0.684 (Powertrain) to 0.699 (Electrical), a spread of only 0.015. By 2024, this range was even narrower: from 0.647 (Powertrain) to 0.672 (Chassis), merely a 0.025 difference. Median overall efficiencies are similarly clustered around 0.66–0.69 for all sectors in all years. These findings suggest that no supplier sector has a clear advantage in total two-stage efficiency. The slight stage-wise differences noted earlier (high Stage 1 for Trim vs. high Stage 2 for Powertrain, etc.) effectively balance out in the overall metric. In other words, sectors that excel in internal operations often have lower external efficiency, whereas sectors that struggle internally tend to compensate with better external outcomes. The end result is a form of equilibrium where all sectors achieve roughly the same composite efficiency when both stages are considered. This indicates that improving overall sustainable supply chain efficiency will require balanced enhancements in both stages, as every sector appears to face its own trade-offs that bring its total performance to a similar level.

Figure 2 visually reinforces the sectoral efficiency patterns summarized in Tables 3–5. Consistent with the tabulated medians, Stage 1 efficiency is uniformly high across all sectors, with median internal scores around 0.85 or above and relatively narrow interquartile ranges.

In contrast, Stage 2 efficiency is substantially lower and more variable, with median values roughly between 0.35 and 0.45, wider IQRs, and frequent low outliers—particularly in the Trim sector. Overall efficiency distributions are tightly clustered at approximately 0.66 for all sectors, showing minimal dispersion. This distributional view highlights that while slight sectoral distinctions exist in internal or external efficiency (e.g., Trim's marginally higher internal median, Powertrain's higher external median), total two-stage efficiency remains remarkably similar across supplier categories, underscoring the balancing effect between the two stages.



Figure 2. Distribution of DEA efficiency scores (stage 1, stage 2, and overall) across supplier sectors and years (2021–2024). Boxplots display medians, interquartile ranges (IQRs), and outliers for Stage 1 (internal operations), Stage 2 (external outcomes), and Overall (two-stage network) efficiency.

3.3. Time-Series Trend Analysis (2021–2024)

This section examines the temporal evolution of efficiency scores from 2021 to 2024, highlighting sector-level patterns and differences across the stage-wise efficiencies of the two-stage network DEA model. Figure 3 presents the time-series trends of median efficiency for each supplier sector (Powertrain, Body, Chassis, Trim, Electrical) from 2021 to 2024.

In each panel, the colored lines represent Stage 1 (internal operations), Stage 2 (external outcomes), and Overall (two-stage network) efficiency. This layout enables a sector-by-sector comparison of temporal patterns.

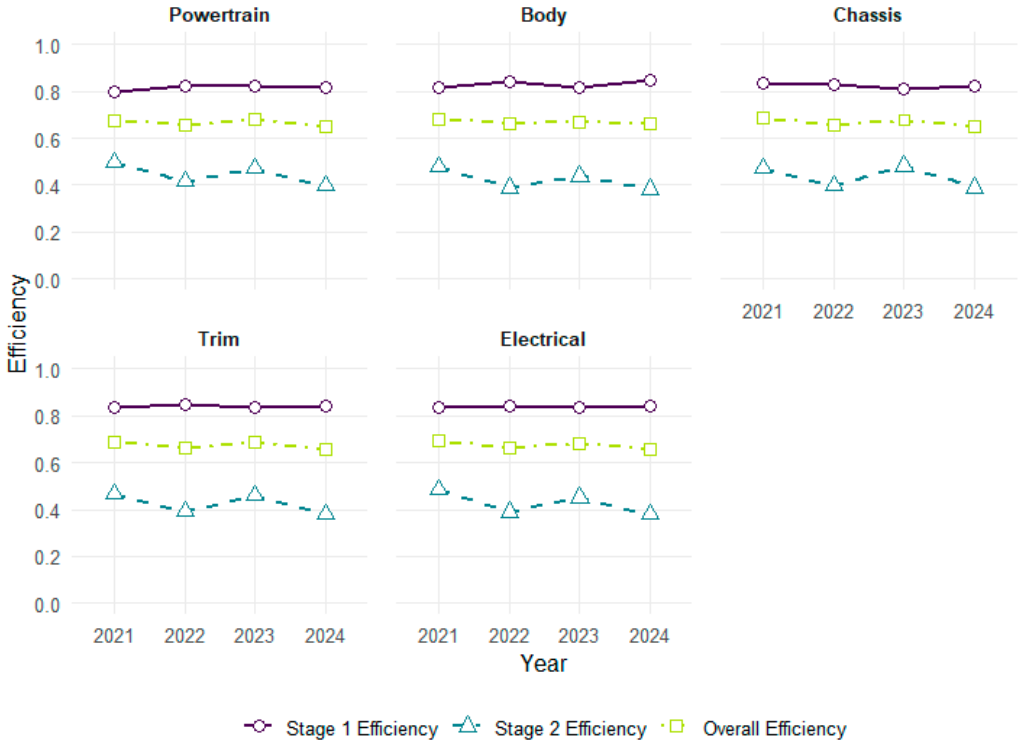


Figure 3. Time-series trends of median efficiency by sector from 2021 to 2024. Each panel represents one supplier sector (Powertrain, Body, Chassis, Trim, Electrical). Colored lines indicate Stage 1 (internal operations), Stage 2 (external outcomes), and Overall (two-stage network) efficiency. Stage 1 efficiency remains high and stable across years in all sectors, whereas Stage 2 efficiency is lower and more variable, and Overall efficiency follows Stage 2's pattern with smaller fluctuations.

Across all sectors, Stage 1 efficiency remains consistently high throughout the period, with median values around 0.85 or above. Year-to-year fluctuations are minimal—generally within a few percentage points—indicating stable and mature internal operations. For example, Trim suppliers, one of the top performers in Stage 1, improved slightly from 0.859 in 2021 to 0.876 in 2022, then remained in the mid-0.87 range through 2024. Other sectors, such as Powertrain and Body, showed similar stability, with only minor shifts.

By contrast, Stage 2 efficiency is lower and more volatile in every sector. All sectors experienced a sharp decline in 2022 compared to 2021, a partial recovery in 2023, and another downturn in 2024. This synchronous pattern strongly suggests that external factors—such as market disruptions or demand shocks—affected all suppliers similarly. For instance, the efficiency of Powertrain Stage 2 fell from 0.465 in 2021 to 0.387 in 2022, rebounded to 0.442 in 2023, then dropped again to 0.357 in 2024. Even sectors showing a stronger recovery in 2023, like Chassis, ultimately followed the same downward trend in 2024.

Overall efficiency trends for each sector closely follow those of Stage 2, albeit with smaller magnitudes of change. High Stage 1 efficiency helped buffer the impact of Stage 2 volatility, so the overall peak-to-trough differences were only about 0.02–0.03 compared to 0.08–0.10 for Stage 2. For example, Body's overall efficiency was 0.685 in 2021, dipped to 0.661 in 2022, rose to 0.673 in 2023, and returned to 0.656 in 2024. Across sectors, the overall efficiency lines remain tightly clustered in each year, confirming that the relative ranking of sectors did not change significantly during the study period.

In summary, the sector-level panels in Figure 3 demonstrate that internal operations efficiency was uniformly high and steady, while external outcomes efficiency declined in specific years due to broader, industry-wide factors. This collective movement led to modest declines in overall sustainable supply chain efficiency by 2024, with all sectors following a similar trajectory. These findings are consistent with international evidence that upstream efficiency does not necessarily translate into downstream performance (e.g., Tavana et al. [21]; Kim and Kim [4]). Our study extends this literature by providing large-scale longitudinal benchmarks of financial sustainability, demonstrating synchronized downturns in Stage-2 efficiency across all sectors in 2022 and 2024.

3.4. Statistical Significance Testing

To rigorously assess the observed differences, we conducted formal statistical tests for stage-wise, year-wise, and sector-wise comparisons. Table 6 summarizes the results of these tests, including one-way ANOVA, non-parametric Kruskal–Wallis, Wilcoxon signed-rank (paired), and Mann–Whitney U (unpaired) tests as appropriate. We tested three main hypotheses: (1) differences between Stage 1, Stage 2, and Overall efficiency; (2) differences across the four years; and (3) differences across the five sectors.

Table 6. Summary of hypothesis test results for efficiency differences (2021–2024).

Comparison	Test	*p*-Value
Stage 1 vs. Stage 2 (efficiency scores)	Wilcoxon signed-rank (paired)	<0.001 **
Stage 1 vs. Overall efficiency	Wilcoxon signed-rank (paired)	<0.001 **
Stage 2 vs. Overall efficiency	Wilcoxon signed-rank (paired)	<0.001 **
2021–2024 (Stage 2 efficiency)	Kruskal–Wallis (df = 3)	<0.001 **
2021–2024 (Overall efficiency)	Kruskal–Wallis (df = 3)	<0.001 **
Among sectors (Overall efficiency, 2024)	ANOVA F (4786) = 0.54	0.71 (n.s.)
2021 vs. 2024 (Stage 2, Overall efficiency)	Mann–Whitney U (unpaired)	<0.001 **

Note: n.s. = not significant ($p > 0.05$); ** = statistically significant at the 1% level (or better).

The stage-to-stage comparisons confirm that the differences between internal and external efficiency are statistically highly significant. A Wilcoxon signed-rank test (for paired data, treating each supplier's Stage 1 and Stage 2 scores as a pair) was performed for each year, and in all cases Stage 1 efficiency was significantly greater than Stage 2 efficiency ($p < 0.001$). Table 6 aggregates this result (all years combined)—clearly, suppliers' internal operations efficiency outpaces their external outcome efficiency to a degree that is unlikely due to random chance. Similarly, Stage 1 vs. Overall and Stage 2 vs. Overall efficiency differences are significant ($p < 0.001$). This indicates that the Overall network efficiency measure is not simply equal to either stage's efficiency: it is significantly lower than Stage 1 (since Overall is dragged down by the weaker external performance) but still higher, on average, than Stage 2. In practical terms, these statistical tests reinforce the earlier observation that internal efficiency is superior to external efficiency across the board. Nearly every supplier has Stage 1 > Stage 2, and even the few exceptions are not enough to alter the overall conclusion. Being efficient in internal operations does not automatically mean a firm is efficient in market outcomes, and this gap is both practically large and statistically robust.

When examining year-to-year differences, we find significant changes over time in external and overall efficiency, but only minor changes in internal efficiency. A Kruskal–Wallis test (non-parametric ANOVA) for equality of medians across 2021–2024 was highly significant for Stage 2 efficiency (χ^2 with df = 3, $p << 0.001$) and for Overall efficiency ($p << 0.001$). This confirms that the efficiency score distributions in 2022 (for example) were not the same as in 2021 or 2024. Follow-up pairwise Mann–Whitney U tests between specific years indicate where those differences lie; for instance, comparing 2021 vs. 2024

yields $p < 0.001$ for Stage 2 efficiency (Table 6) and similarly for Overall efficiency, verifying that the drop from the beginning to the end of the study period is statistically significant. By contrast, Stage 1 efficiency showed much less variation—the Kruskal–Wallis test for Stage 1 was marginally significant ($p \approx 0.0013$, not tabulated above), which, given the large sample sizes, suggests a very slight shift in the distribution over four years. In practical terms, the mean Stage 1 efficiency increased by only about 0.01–0.02 in 2022 and stayed nearly flat thereafter (Table 2). Thus, while this small increase was detected as statistically non-zero (perhaps due to 2022 being a particularly strong year internally), it has limited practical significance. We conclude that there was no substantial time trend in internal efficiency, whereas external efficiency underwent a significant decline (especially in 2022 and 2024), driving a similar significant decline in overall efficiency. These statistical findings are consistent with the visual trends in Figure 2 and the descriptive stats: the years 2022 and 2024 were indeed significantly worse than 2021 for suppliers' external and overall performance (at the 99.9% confidence level or higher).

Finally, sector-to-sector comparisons reveal no statistically significant differences in efficiency among the five supplier sectors. As shown in Table 6, a one-way ANOVA on overall efficiency by sector (illustrated for 2024) resulted in $F(4786) = 0.54$, $p = 0.71$, indicating no meaningful difference in mean overall efficiency across Powertrain, Body, Chassis, Trim, and Electrical sectors. We obtained similar ANOVA results for other years and for Stage 1 and Stage 2 efficiencies (all $p > 0.3$, not individually listed in the table). Non-parametric tests concur; for example, a Kruskal–Wallis test on Stage 2 efficiency by sector in 2021 yielded $p \approx 0.84$ (no significant difference). In short, the small numerical differences observed in Tables 3–5 (e.g., Powertrain vs. Trim) do not pass significance thresholds once variability is accounted for. The lack of sector significance suggests that any efficiency advantage one sector appears to have is not statistically distinguishable given the sample distribution. For instance, while Powertrain suppliers showed the highest mean Stage 2 efficiency in multiple years, the variation within each sector's scores is large enough that we cannot conclusively say Powertrain firms, as a group, perform better externally than, say, Electrical or Body firms. The consistency of overall efficiency across sectors is especially reflected in the statistical insignificance—all sectors are statistically on par in total efficiency. This finding reinforces our earlier interpretation: the apparent performance trade-offs between Stage 1 and Stage 2 leave all sectors with roughly equal overall efficiencies, so it is unsurprising that formal tests find no sector to be significantly ahead or behind.

In summary, the statistical tests corroborate our key results. Internal vs. external efficiency gaps are highly significant, underscoring an important performance imbalance within the two-stage supply chain process. Temporal analysis confirms that the efficiency downturns in 2022 and 2024 were real and industry-wide (not random noise), especially for external outcomes. Conversely, differences across supplier sectors are statistically negligible, indicating a level playing field in aggregate efficiency—any slight sectoral performance differences in one stage are offset in the other stage or are within normal variability. These insights, derived from rigorous hypothesis tests, add confidence to the substantive conclusions of our study: to improve sustainable supply chain efficiency, firms and policymakers should focus on boosting Stage 2 (external) performance and resilience—the area where weaknesses and variability are evident—while maintaining the uniformly high Stage 1 operations, and they should do so across the entire supplier network rather than targeting any single sector, since all sectors face similar efficiency challenges.

3.5. Robustness Checks

To examine the robustness of our findings, we conducted a series of sensitivity analyses. First, we replaced Stage-2 outputs with alternative measures such as operating income and return on assets (ROA). Second, we applied different treatments of outliers, including winsorization at the 1% tails and a $\pm 1.5 \times$ IQR rule. Across these alternative specifications, the central patterns remained unchanged. Stage-1 efficiency continued to be consistently high and stable, while Stage-2 efficiency was lower, more volatile, and displayed synchronized downturns in 2022 and 2024. Overall efficiency still closely mirrored Stage-2, and no statistically significant differences across sectors were observed. These results confirm that the observed trends are not artifacts of the chosen output variables or outlier handling methods but rather reflect systematic characteristics of the supplier network.

4. Discussion

This study applied a SCOR-based two-stage NRAM DEA model to a large panel of Korean automotive suppliers from 2021 to 2024, enabling a stage-specific assessment of sustainable supply chain efficiency. The analysis revealed two consistent patterns. First, Stage 1 (internal operations) efficiency was uniformly high and stable across all sectors and years, indicating that lean production, cost control, and asset utilization practices are deeply embedded in the industry. This stability mirrors earlier findings in both Korean and global automotive contexts, where mature operational systems such as lean and just-in-time have driven sustained internal performance. The minimal year-to-year variation further suggests that internal operations have reached a performance plateau, and transformative innovations—rather than incremental changes—may be required for further improvement. Second, Stage 2 (external outcomes) efficiency was lower, more volatile, and exhibited synchronized downturns in 2022 and 2024 across all sectors. These downturns are plausibly linked to external macroeconomic and geopolitical events, including global demand realignment, raw material price spikes, and supply disruptions during post-pandemic recovery. Explicitly connecting these synchronized declines to systemic shocks enhances the explanatory value of the findings. The trends of sectoral synchronicity in Stage 2 point to systemic factors as the primary drivers of external inefficiency, rather than sector-specific shortcomings.

From a theoretical standpoint, the observed contrast between stable Stage-1 efficiency and volatile Stage-2 efficiency can be interpreted through dynamic capabilities theory. High Stage-1 efficiency reflects deeply embedded operational routines and resource configurations [33], whereas fluctuating Stage-2 outcomes underscore the need for adaptive capabilities such as demand sensing, seizing opportunities, and strategic reconfiguration to cope with external shocks [34–36]. This interpretation situates our findings within the broader conceptual landscape of supply chain resilience, which highlights the interplay of structural routines and adaptive responsiveness [37–39]. At the same time, the absence of statistically significant differences in overall efficiency among sectors suggests that structural features of the Korean automotive supply chain—such as high interdependence among suppliers and OEMs and shared exposure to systemic shocks—tend to offset sector-level variations.

These results also reflect structural characteristics of the Korean automotive sector. The dominance of OEMs, long-term relational contracts, and standardized production systems creates a tightly coupled supplier–buyer network. Such interdependence explains the muted sectoral differences in efficiency but also amplifies vulnerability to systemic shocks, as seen in the synchronized downturns of Stage 2. From a sustainability perspective, Stage-1 resilience and Stage-2 responsiveness should be regarded not merely as technical

outcomes but as structural capabilities that help stabilize employment, maintain supply continuity, and mitigate environmental inefficiencies during disruptions.

While the broad pattern of higher Stage-1 efficiency relative to Stage-2 has been noted in prior DEA research, our study extends this evidence in three ways: (i) applying the model to a large four-year national panel (770–790 suppliers annually), enabling robust longitudinal benchmarking; (ii) identifying synchronized Stage-2 downturns linked to systemic shocks, providing empirical evidence of resilience challenges; and (iii) interpreting the Stage-1 vs. Stage-2 divergence through resilience and dynamic capabilities theory, thereby embedding the results in sustainability debates rather than treating them as purely technical findings.

In this light, our study contributes to sustainable supply chain management by distinguishing between operational efficiency and financial sustainability. Although the current model primarily addresses the economic dimension, Stage-1 resilience and Stage-2 responsiveness also provide a foundation for environmental and social outcomes—for example, enabling leaner operations that reduce waste and emissions and support stable employment [1,2,40].

A key limitation of this study is its reliance on financial outputs (revenue and net income) at Stage 2, which restricts the analysis to the economic pillar of sustainability. We acknowledge this limitation and suggest that future research incorporate environmental indicators (e.g., emissions, energy use) and social measures (e.g., labor practices, employee well-being) once reliable firm-level data are available. Nonetheless, checks for the robustness of data with alternative financial indicators confirm the stability of the efficiency patterns reported here.

Another limitation relates to inference. Although bootstrap procedures [41–44] are widely recommended to correct the downward bias in DEA efficiency scores, their primary role is to address inward-frontier bias when DMUs are relatively limited. In our case, the DMU-to-variable ratio was very large, substantially mitigating this bias. Consequently, while bootstrap bias-correction could be performed, it would not materially change our conclusions. Moreover, rigorous bootstrap methods for network DEA, particularly for decomposed stage-level efficiencies under linking constraints, are still underdeveloped in the literature. We therefore acknowledge this as an area for methodological development and suggest that future work adapt emerging bootstrap approaches to the network setting for more comprehensive inference.

Future studies could extend this analysis by integrating environmental and social sustainability metrics to capture triple-bottom-line performance, examining causal links between macroeconomic conditions and Stage-2 outcomes, and assessing how digital transformation initiatives affect the balance between internal efficiency and external responsiveness. In addition, further work could explore how Stage-1 resilience and Stage-2 adaptability jointly contribute not only to profitability but also to environmental and social sustainability, such as through more efficient resource utilization, reduced waste, and strengthened supplier–customer relationships.

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