International Journal of Applied Operational Research
Vol. 14, No. 1, pp. 1-9, Winter 2026

Journal homepage: ijorlu.liau.ac.ir

A method for estimating the returns to scale of two-stage supply chains using intermediate data

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Received: 2 November 2025 ; **Accepted:** 20 December 2025

Abstract: Estimating the returns to scale (RTS) of two-stage supply chains is a critical topic in Data Envelopment Analysis (DEA). Traditional black-box DEA models calculate RTS by ignoring intermediate data—the essential connecting factors between production stages—which can lead to biased and unreliable evaluations. To address this limitation, this paper proposes a novel method for estimating the overall system's RTS in a dependent state. By building upon the CCR coverage form model introduced by Banker et al., the proposed approach strictly maintains the internal structural relationship between the first and second stages. Specifically, the RTS of the first stage is estimated initially, and these output changes are then incorporated as input constraints for the second stage to determine the overall system's RTS. The practical applicability of this proposed method is demonstrated using an empirical dataset of 24 non-life insurance companies in Taiwan. The findings reveal that the dependent model is more restrictive and logically consistent than the independent approach; whenever the overall RTS in the dependent state is constant, at least one of the individual stages also exhibits constant RTS. Ultimately, incorporating intermediate data provides managers and policymakers with a more robust, realistic evaluation tool for capacity planning and resource allocation in complex, multi-stage production environments.

Keyword: Data envelopment analysis, returns to scale, supply chain, efficiency.

1 Introduction

Data envelopment analysis (DEA) is a non-parametric method used to evaluate the relative efficiency of decision-making units. The first DEA model was introduced by Charnes, Cooper, and Rhodes and was known as the CCR model [1] with constant returns to scale. Banker, Charnes, and Cooper introduced the BCC model by modifying the CCR model,

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[DOI: 10.71885/ijorlu-2026-1-741]

which has a variable returns to scale [2]. These models have been used to estimate the returns to scale of decision-making units, including supply chains. A supply chain is a system consisting of organizations, individuals, activities, information, and resources that collaborate in the delivery of a product or service to the consumer [3]. The first DEA model with a supply chain (network) structure was employed by Charnes et al [4]. This model was later developed by other researchers such as Lovell et al [5], Seiford [6], Sexton et al [7] and Patrizii [8].

In order to estimate the returns to scale of a decision-making unit located on the efficient frontier, Banker and Thrall [9], presented a method using the optimal solution of the CCR DEA model for that unit. Banker et al introduced another model in using the CCR DEA model and without the requirement of the presence of an efficient decision-making unit [2]. Zho [10] proposed a method using a comparison of efficiency scores of the CCR and BCC models in the DEA framework. He showed that if the efficiency scores of a decision-making unit under investigation are the same in both models, the returns to scale of the decision-making unit is constant, and otherwise, the returns to scale is estimated based on the optimal values of λj^*. Fare and Grosskopf [11] also presented a model for estimating the returns to scale of a decision-making unit using the efficiency scores of the three models: CCR- BCC, and BCC-CCR.

To analyze the performance of the two-stage network systems, the key issues are measuring the overall efficiency and returns to scale of the system, identifying divisional efficiencies of the two stages, and obtaining frontier projections for the inefficient units. The growing literature on network DEA show different approaches (see, e.g., Kao & Hwang, [12], Li et al., [13, 14], Liu et al., [15], Liang et al., [16], Lim & Zhu, [17, 18], Yin et al [19], Guo et al [20], Ahangary et al [21]) to network DEA. However, the existing approaches have not provided a clear theoretical basis and suffered some key pitfalls of network DEA. For instance, the primal-dual correspondence no longer holds for network DEA models, uncertainties exist when determining the divisional efficiencies, and the practical interpretation of the frontier projection process is not clear [22].

The aim of this paper is to present a method for estimating the returns to scale of two-stage supply chains using the CCR coverage form model used by Banker et al [9]. The difference with previous methods is that intermediate data will also play an undeniable role. The advantage of this method is that the results obtained in the dependent state for the entire chain are more believable than the results in the independent state.

The main contributions of this paper are summarized as follows:

• Theoretical Advancement: Generalizing Banker et al.'s method to estimate the RTS of two-stage supply chains while strictly preserving the connection between stages via intermediate data.

• Methodological Accuracy: Developing a dependent two-stage DEA model that calculates overall scale efficiency based on the simultaneous impact of stage-specific factors, overcoming the limitations of traditional 'black box' RTS estimations.

• Practical Application: Providing empirical evidence that dependent stage modeling yields more reliable and logically consistent RTS classifications compared to independent models.

The structure of this paper is organized as follows. In the next section, the models that are used to estimate the returns to scale of one decision making unit are introduced. In section 3, the proposed dependent two-stage model is introduced and the returns to scale of the whole system is estimated using data envelopment analysis methods.

[DOI: 10.71885/ijorlu-2026-1-741]

2 Returns to scale of two-stage supply chains

Suppose that we have n DMUs, and each DMUj (j=1, 2, …, n) has m inputs to the first stage, Xij, (i=1, 2, … m), and q outputs from this stage, Zpj, (p=1, 2, …, q). These q outputs then become the inputs of the second stage. The outputs of this stage are denoted Yrj, (r=1, 2, …, s).

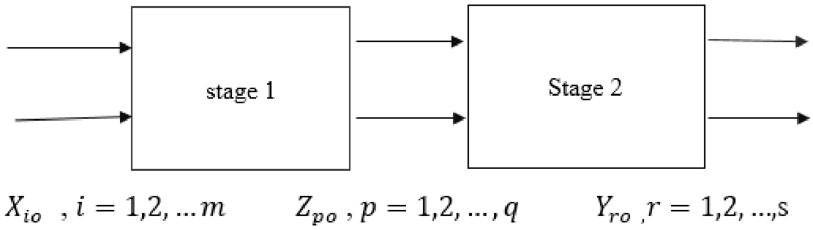

Fig. 1 Two stage Supply chain with input X, outputs Y, and intermediate data Z(DMUo).

Now consider a two stage supply chain DMUo. Zpo, p=1, 2, …, q are intermediate data, that are the outputs of the first stage and the inputs of the second stage (see Figure 1). In fact, decision unit o consumes input Xio, i=1, 2, … m, and generates intermediate data, Zpo, p=1, 2, …, q. Then, all outputs of the first stage are used as inputs of the second stage, and the second stage products Yro, r=1, 2, …, s are produced. The application of the model by Banker and Thrall (1992), for estimating the returns to scale of a two-stage supply chain and in the case where intermediate data do not play a role (independent case) involves solving the following models. First, we solve the following model:

$$
\begin{aligned}
& Min\ \theta \\
& \text{st .}\ \sum_{j=1}^{n} \lambda_j X_{ij} \le \theta X_{io} \qquad i = 1,2 \dots, m \ , \\
& \qquad \sum_{j=1}^{n} \lambda_j Y_{rj} \ge Y_{ro} \qquad r = 1,2, \dots, s \ , \\
& \qquad X_{ij} \ge 0 \ , \ Y_{rj} \ge 0 \ .
\end{aligned}
\tag{1}
$$

Now:

a) If $\sum_{j=1}^{n} \lambda_j^{\ *} = 1$, we can conclude that the returns on a unit scale is constant.

b) If $\sum_{j=1}^{n} \lambda_j^{\ *} < 1$, we solve the following model:

$$
\begin{aligned}
& \lambda^{+} = Max\ \sum_{j=1}^{n} \lambda_j \\
& \quad st\ .\ \sum_{j=1}^{n} \lambda_j X_{ij} \le \theta^{*} X_{io} \qquad i = 1,2 \dots, m, \\
& \qquad\quad \sum_{j=1}^{n} \lambda_j Y_{rj} \ge Y_{ro} \qquad r = 1,2, \dots, s, \\
& \qquad\quad \sum_{j=1}^{n} \lambda_j \le 1 \ .
\end{aligned}
\tag{2}
$$

If $\lambda^{+} < 1$, the returns to scale of unit is increasing.

c) If $\sum_{j=1}^{n} \lambda_j^{\ *}$>1,, we solve the following model:

$$
\begin{aligned}
& \lambda^{-} = Min \sum_{j=1}^{n} \lambda_j \\
& \quad st \quad \sum_{j=1}^{n} \lambda_j X_{ij} \le \theta^{*} X_{io} \qquad i = 1,2 \dots, m \ , \\
& \qquad\quad \sum_{j=1}^{n} \lambda_j Y_{rj} \ge Y_{ro} \qquad r = 1,2, \dots, s, \\
& \qquad\quad \sum_{j=1}^{n} \lambda_j \ge 1.
\end{aligned}
\tag{3}
$$

If λ^{-} be greater than one, the returns to scale of unit is decreasing.

As can be observed, intermediate data are not taken into account when estimating the return to scale of whole system.

[DOI: 10.71885/ijorlu-2026-1-741]

3 Estimating returns to scale of two stage supply chain in the dependent state

In the independent state, there is no relation between the returns to scale of the first and second stages, and the returns to scale of each stage as well as the whole returns to scale are estimated independently. For a more accurate estimation, a model should be presented that establishes the relationship between the two stages and the whole stage.

Recent methodological advancements increasingly emphasize the necessity of modeling the internal linkages within network technologies. Contemporary studies (e.g., Ahangary et al. [21]; Fakhr Mousavi et al.[23]), alongside the most recent developments in 2024 and 2025 (Peykani et al. [24]; Chen & Wang [25]; Koushki & Naghdehforoushha [26]), strongly highlight that ignoring intermediate variables in complex supply chains leads to biased scale elasticity and overall efficiency estimates. By treating the two-stage process as a cohesive network technology rather than isolated black boxes, the proposed methodology explicitly incorporates intermediate products. This dependent approach ensures that the output targets of the first stage match the resource constraints of the second stage, structurally aligning with the fundamental realities of modern supply chain operations and providing a more robust mathematical foundation for RTS estimation.

Now, consider the DMUo. In the first step, and in accordance with the Banker model [9], we estimate the returns to scale in the first stage. For this purpose, the following model is solved:

$$
\begin{aligned}
& Min\ \theta \\
& st.\ \sum_{j=1}^{n} \lambda_j X_{ij} \le \theta X_{io} \qquad i = 1,2 \dots, m \\
& \qquad \sum_{j=1}^{n} \lambda_j\ Z_{pj} \ge Z_{PO} \qquad p = 1,2, \dots, q \\
& \qquad X_{ij} \ge 0\,,\ Z_{pj} \ge 0
\end{aligned}
$$

Similarly, with equations (1,2,3), we obtain the values of $\theta^*, \sum_{j=1}^{n} \lambda_j{}^*\ and \lambda^+\ or\ \lambda^-$. $\left(if\ \sum_{j=1}^{n} \lambda_j{}^* \ne 1\right)$.

This paper attempts to consider the relationship between the two stages in estimating the whole returns to scale, the output changes of the first stage are considered as the input changes of the second stage. This shows how much the input changes in the first stage cause changes in the output of the second stage. After solving the models related to the first stage, we consider the second stage model as the whole (dependent) model by taking into account the results of the first stage.

$$
\begin{aligned}
& Min\ \alpha \\
& st.\ \sum_{j=1}^{n} \lambda_j X_{ij} \le \theta^* X_{io} \qquad i = 1,2 \dots, m\,, \\
& \qquad \sum_{j=1}^{n} \lambda_j\ Z_{pj} \ge Z_{Po} \qquad p = 1,2, \dots, q, \\
& \qquad \sum_{j=1}^{n} \mu_j Z_{pj} \le \alpha Z_{Po} \qquad p = 1,2 \dots, q\,, \\
& \qquad \sum_{j=1}^{n} \mu_j Y_{rj} \ \ge Y_{ro} \qquad r = 1,2, \dots, s\,, \\
& \qquad Y_{rj} \ge 0\,,\ Z_{pj} \ge 0\,, X_{ij} \ge 0\,.
\end{aligned}
$$

$a)\ if\ \sum_{j=1}^{n} \mu_j{}^* = 1$, it can be concluded that the returns to scale is constant.

b) if $\sum_{j=1}^{n} \mu_j{}^* < 1$, solve the following model :

$$
\begin{aligned}
& \mu^+ = Max\ \sum_{j=1}^{n} \mu_j \\
& st.\quad \sum_{j=1}^{n} \mu_j Z_{pj} \le \alpha^* Z_{Po} \qquad p = 1,2 \dots, q\,, \\
& \qquad \sum_{j=1}^{n} \mu_j Y_{rj} \ \ge Y_{ro} \qquad r = 1,2, \dots, s\,, \\
& \qquad \sum_{j=1}^{n} \mu_j \le 1\,.
\end{aligned}
$$

If $\mu^+ < 1$, the returns to scale of unit is increasing.

c) if $\sum_{j=1}^{n} \mu_j{}^{*} > 1$, , solve the following model:
$\mu^{-} = Min \sum_{j=1}^{n} \mu_j$
St . $\sum_{j=1}^{n} \mu_j Z_{pj} \leq \alpha^{*} Z_{Po} \qquad p = 1,2 \dots, q$,
$\sum_{j=1}^{n} \mu_j Y_{rj} \geq Y_{ro} \qquad r = 1,2, \dots, s$,
$\sum_{j=1}^{n} \mu_j \geq 1$.
If μ^{-} be greater than1, returns to scale is decreasing.
In this case, it is observed that the median data also play a role.

4 Example: Taiwan insurance companies

Kao and Huang provided data on 24 non-life insurance companies in Taiwan [12].

Table 1 Inputs (X), intermediate data (Z) and outputs (Y) of the 24 non-life insurance companies in Taiwan.

	Operation expenses (X1)	Insurance expenses (X2)	Direct written premiums (Z1)	Reinsurance premiums (Z2)	Underwriting profit (Y1)	Investment profit (Y2)
1. Taiwan fire	1178744	673512	7451757	856735	984143	681687
2. Chung Kuo	1381822	1352755	10020274	1812894	1228502	834754
3. Tai ping	1177494	592790	4776548	560244	293613	658428
4. China mariners	601320	594259	3174851	371863	248709	177331
5. Fubon	6699063	3531614	37392862	1753794	7851229	3925272
6. Zurich	2627707	668363	9747908	952326	1713598	415058
7. Taian	1942833	1443100	10685457	643412	2239593	439039
8. Ming tai	3789001	1873530	17267266	1134600	3899530	622868
9. central	1567746	950432	11473162	546337	1043778	264098
10. the first	1303249	1298470	8210389	504528	1697941	554806
11. Kou hua	1962448	672414	7222378	643178	1486014	18259
12. union	2592790	650952	9434406	1118489	1574191	909295
13. shanking	2609941	1368802	13921464	811343	3609236	223047
14. south china	1396002	988888	7396396	465509	1401200	332283
15. Cathay century	2184944	651063	10422297	749893	3355197	555482
16. Allianz president	1211716	415071	5606013	402881	854054	197947
17. newa	1453797	1085019	7695461	342489	3144484	371984
18. AIU	757515	547997	3631484	995620	692731	163927
19. North America	159422	182338	1141950	483291	519121	46857
20. federal	145442	53518	316829	131920	355624	26537
21. royal & sun alliance	84171	26224	225888	40542	51950	6491
22. Asia	15993	10502	52063	14574	82141	4181
23. AXA	54693	28408	245910	49864	0.1	18980
24. Mitsui Somitomo	163297	235094	476419	644816	142370	16976

[DOI: 10.71885/ijorlu-2026-1-741]

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Returns to scale (RTS), has been estimated using model (1) for independent first stage, independent second stage, and whole system. Return to scale has also been estimated using model (2,3) for dependent whole stage and presented in the table. Denote DRS, IRS and CRS as the decreasing, increasing and constant returns to scale, respectively.

Table 2 Returns to scale of two stages and whole system (independent and dependent state).

Unit	RTS of first stage	RTS of second stage	whole RTS (independent)	whole RTS (dependent)
1. Taiwan fire	DRS	CRS	CRS	DRS
2. Chung Kuo	DRS	DRS	CRS	DRS
3. tai ping	DRS	CRS	CRS	CRS
4. China mariners	CRS	DRS	IRS	DRS
5. Fubon	CRS	CRS	CRS	CRS
6. Zurich	IRS	DRS	CRS	DRS
7. Taian	DRS	DRS	DRS	DRS
8. Ming tai	DRS	DRS	DRS	DRS
9. central	CRS	DRS	DRS	IRS
10. the first	CRS	DRS	IRS	DRS
11. KuoHua	IRS	DRS	DRS	DRS
12. union	CRS	DRS	CRS	DRS
13. ShingKong	DRS	DRS	DRS	DRS
14. south China	CRS	DRS	DRS	DRS
15. Cathay century	CRS	DRS	CRS	DRS
16. Allianz president	IRS	DRS	DRS	DRS
17. Newa	CRS	CRS	DRS	CRS
18. AIU	DRS	DRS	DRS	DRS
19. North America	CRS	DRS	DRS	DRS
20. federal	IRS	DRS	DRS	DRS
21. royal & Sun alliance	IRS	CRS	CRS	IRS
22. Asia	IRS	CRS	CRS	CRS
23. Axa	IRS	CRS	CRS	IRS
24. Mitsui Sumitomo	CRS	DRS	DRS	DRS

5 Results and Discussion

5.1 Comparison of returns to scale in independent and dependent states

In the dependent model, units 3, 5, 17 and 22 are efficient (and have constant returns to scale). In the independent model, units 1, 2, 3, 5, 6, 12, 15, 21, 22, and 23 are efficient (but only units 2, 5, 12, and 21 have constant returns to scale). This indicates that the dependent model is more restrictive and has more stringent criteria.

All efficient units in the dependent model are MPSS (Most productive scale size). The independent model has the same number of MPSS units as the dependent model, even though it has more efficient units. In the first stage, we have four MPSS (9, 12, 15, 19). In the second stage, we also have four MPSS (3, 5, 17, 22). Therefore, the number of MPSS is the same in all stages.

No unit is MPSS in both the dependent and independent states at the same time. Out of 24 units under consideration, only units 1 and 3 have similar returns to scale in both stages of the dependent model. This happens in the independent state as well, but not in the dependent state.

Units 2, 5, 8, 13, 17, and 18 have the same returns to scale in both stages of the dependent model. The whole returns to scale in the dependent state are similar to the previous two stages, but this is not necessarily the case in the independent state. For example, unit 17 has a constant returns to scale in both the first and second stages, but in the independent model, the returns to scale are decreasing. Similarly, unit 2 has a constant returns to scale in the first and second stages of the independent model, but in the dependent model, the returns to scale are decreasing.

Except for unit 2, the returns to scale for other units 8, 13, and 18 are decreasing in both the first and second stages, as well as in both the independent and dependent states.

For unit 5, the returns to scale are constant in the first, second, independent, and dependent states. Whenever the whole returns to scale are constant in the dependent state, returns to scale in one of the first or second stages must have been constant (units 3, 5, 17, 22). However, there are cases where the whole returns to scale in the independent state are constant, and none of the first and second stages have constant returns to scale (units 2, 8, 13, 18).

5.2 Discussion

The findings of this study validate the hypothesis that intermediate data play a critical role in accurately estimating the overall returns to scale of a two-stage supply chain. Unlike traditional black-box models (e.g., standard CCR and BCC approaches) which often classify units with conflicting stage-level RTS into arbitrary overall categories, the proposed dependent model aligns the system's overall RTS with the behavior of its internal stages. For instance, while Kao and Hwang [12] initiated the decomposition of two-stage efficiency, their early approach did not fully integrate simultaneous RTS behavior across stages. Our results demonstrate that when the overall returns to scale in the dependent model are constant, at least one of the individual stages (first or second) must also exhibit constant returns to scale. This structural consistency is conspicuously absent in independent evaluations. Furthermore, these findings are consistent with recent advancements in network DEA (such as Amirteimoori et al. [27], and Fakhr Mousavi et al. [23]), which argue that divisional efficiencies strictly govern overall system performance. The restrictive nature of the dependent model, which yields fewer overall efficient units compared to the independent approach, confirms that preserving the production stage connections provides a more rigorous, realistic, and reliable benchmarking framework for managerial decision-making.

6 Conclusion

Estimating the returns to scale of a decision-making unit plays an important role in improving the efficiency of that unit. The ultimate goal of a decision-making unit is to become a unit with maximum productivity, and this goal cannot be achieved without correcting or fixing the unit's scale. Supply chains are no exception to this rule. The first method invented by researchers for analyzing data coverage was to estimate the return to scale of the supply chain

[DOI: 10.71885/ijorlu-2026-1-741]

without considering intermediate data, which, due to their importance, resulted in unreliable results.
In this paper, an idea was proposed to estimate the return to scale of the supply chain, when intermediate data play a role. First, using the method of Banker, et al., the return to scale of the first stage was estimated, and then by applying the results of the first stage in the model relevant to the second stage, the return to scale of the whole system was estimated, which clearly maintained the relationship between the stages.
To compare the results of estimating the returns to scale of the total supply chain in independent and dependent states, the example of insurance companies presented in [12] was used.

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