

Article

Two-Side Merger and Acquisition Matching: A Perspective Based on Mutual Performance Evaluation Considering the Herd Behavior

Yao Wen ¹ and Hailiu Shi ^{2,*} ¹ School of Economics and Management, Fuzhou University, Fuzhou 350108, China; wenyao@fzu.edu.cn² College of Business Administration, Fujian Jiangxia University, Fuzhou 350108, China

* Correspondence: shihailiu@fjxu.edu.cn

Abstract

A good merger and acquisition (M&A) cannot be achieved without a good matching that not only ensures high satisfaction for both bidders and targets but also operates as a two-sided process based on their mutual evaluations. Previous studies mostly focus on estimating the potential gains, and even those addressing M&A matching or the selection of merger targets and partners overlook the herd behavior of decision makers in the mutual evaluation. Nevertheless, decision makers often adjust their opinions by consulting others' opinions, especially those they trust, and behave bounded rationality. Based on these, we propose a new approach for the two-side M&A matching from a perspective based on the mutual performance evaluation considering herd behavior. First, based on the concept of the cross efficiency in data envelopment analysis field, we propose a mutual evaluation method considering herd behavior of bidders and targets. Then, we measure the bidders' and targets' satisfaction with each other based on the prospect theory. Next, to seek the optimal M&A matching strategy, we build a two-side matching model with two objective functions that maximize the bidders' and targets' satisfaction with each other simultaneously. Finally, we use the data of 51 banks to illustrate our method.

Keywords: mutual evaluation; herd behavior; data envelopment analysis; two-sided matching; bounded rationality

MSC: 90B50; 91E45



Academic Editor: David Carfi

Received: 1 September 2025

Revised: 6 October 2025

Accepted: 11 October 2025

Published: 13 October 2025

Citation: Wen, Y.; Shi, H. Two-Side Merger and Acquisition Matching: A Perspective Based on Mutual Performance Evaluation Considering the Herd Behavior. *Mathematics* **2025**, *13*, 3268. <https://doi.org/10.3390/math13203268>

Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Mergers and acquisitions (M&As) are popular business strategies commonly used by enterprises to expand their scale and enhance market competitiveness [1,2]. A good M&A activity can reduce the costs, increase the profits, and improve the performance of enterprises [2–6]. However, many research studies such as Koi-Akrofi [7] indicate that the failure rate of M&As in recent decades is at least 50 percent (accessed on 9 January 2024. <https://www.investopedia.com/articles/investing/111014/top-reasons-why-ma-deals-fail.asp#:~:text=Losing%20the%20focus%20on%20the%20desired%20objectives,%20failure,lead%20to%20the%20failure%20of%20any%20M&A%20deal>). To improve the M&A activities, the matching of M&A parties including bidders and targets is critical. A good M&A matching should consider the mutual evaluation between the bidders and the targets rather than just the bidders' unilateral evaluation of the targets. At the same time, various evaluation indicators should be considered, not just cost or profit indicators [6]. The

efficiency evaluation can achieve these functions and also take into account the relative competitiveness among the homogeneous enterprises. Therefore, our study aims to seek the M&A matching strategy from a mutual performance evaluation perspective.

For efficiency evaluation, data envelopment analysis (DEA) [8] is a commonly used method. DEA is a data-driven and non-parameter evaluation approach that can be used to evaluate the relative efficiencies of a group of homogeneous decision-making units (DMUs). Also, DEA possesses many advantages compared with other methods such as analytic hierarchy process [9] and stochastic frontier analysis [10]. First, DEA can comprehensively evaluate DMUs containing multiple indicators, including inputs and outputs. Second, DEA is a non-parametric evaluation method that does not require pre-setting the form of the production function. Third, DEA does not require experts to subjectively score the evaluation indicators. It can objectively give the values of the indicator weights by running the mathematical formula. Based on these advantages, researchers make significant theoretical advances, proposing various improved models based on the classic CCR and BCC models. Among these models, the cross-efficiency model [11] can provide mutual evaluation because the cross efficiency is integrated by the self-evaluation and other-evaluation results. Based on this characteristic of cross efficiency, it is widely used to evaluate DMUs' efficiencies, such as the electricity generation and transmission system [12], banks [13], basketball games [14], and firms [15]. Therefore, DEA is a feasible method can be used to evaluate the performance of M&A activities, and the concept of cross efficiency in DEA can be used for mutual evaluation between bidders and targets. Nevertheless, the existing studies on cross efficiency are not entirely applicable to the mutual evaluation of bidders and targets in the M&A activity. Specifically, for the other-evaluation in previous studies on cross efficiency, the herd behavior of decision makers is mostly ignored. In other words, previous studies assume decision makers are completely confident, so each DMU is not influenced by other DMUs' other-evaluation results when evaluating other DMUs. However, in reality, decision makers often lack confidence in their opinions and are easily influenced by the opinions of others, especially the opinions of the those they trust [16–19]. Therefore, it is necessary to construct a novel mutual evaluation method considering the herd behavior, then use it to achieve the two-side M&A matching.

Furthermore, previous studies on efficiency evaluation of M&A activities mostly focus on measuring the potential gains [20–22], which are post-evaluation based on the premise that the matching between bidders and targets is effective. However, in reality, M&A matching has a high failure rate [7], and a good pre-matching is necessary. To improve the M&A, researchers study partner selection of the M&A activities, such as Zhu et al. [2,6] and Chang et al. [1]. These studies provide various solutions to find the optimal partners of M&A, most of which aim at maximizing the overall performance of M&A and rarely consider the mutual evaluation of bidders and targets. Also, a few studies such as Lin et al. [23] and Shi and Wang [24] provide matching strategy for M&A from the perspective of efficiency evaluation. These studies use M&A matching that is a two-side matching that needs to consider being satisfactory to each other. However, these studies on partner selection in M&A activities and the M&A matching ignore the herd behavior of decision makers in the mutual evaluation. As mentioned above, such matching strategy may be not acceptable or not in line with real requirement. In addition, M&A activities are full of risks and uncertainties, so decision makers often behave with bounded rationality when faced with the choice of M&A parties. Accordingly, as studied in Shi and Wang [24], it is necessary to take bidders' and targets' bounded rationality into account for M&A matching. In detail, the utility of bidders and targets depends on the gap between the final outcome and the reference point, rather than just the final outcome itself. In Shi and Wang [24], the reference point is the values of each DMU's inputs and outputs. Nevertheless, another

situation also exists, where the reference point is the self-evaluation result of each DMU. In this study, we provide an M&A matching strategy based on this different situation.

Based on above analyzed literature deficiencies and the real requirement of M&A, we study the research question of how to seek a two-side M&A matching strategy from the perspective based on the mutual performance evaluation considering the herd behavior. First, we use the concept of cross efficiency in the DEA method to obtain the self-evaluation and other-evaluation results of all bidders and targets. Then, based on the herd coefficient that reflects the extent to which a decision maker believes in the opinions of others, we propose a adjust strategy to achieve the mutual performance evaluation considering the herd behavior. Subsequently, we calculate the mutual utility of bidders and targets and use it to measure their satisfaction with each other, where the self-evaluation results are reference points. Next, we construct a new matching model with two objective functions to seek the optimal matching strategy for M&A. Finally, we use the data of 51 banks to validate our proposed method.

Compared with previous studies, this study processes the following three contributions. First, we incorporate the herd behavior of decision makers into the mutual evaluation and propose a new mutual performance evaluation method based on cross-efficiency in the DEA field. Second, we measure bidders' and targets' satisfaction with each other by considering their bounded rationality and using self-evaluation results as reference points, which better reflects real-world conditions. Third, we develop a matching strategy that simultaneously maximizes the satisfaction of both bidders and targets, rather than prioritizing only one side. Based on these contributions, the integration of DEA, herd behavior, and prospect theory provides a new approach to two-side M&A matching strategies that aligns more closely with real-world conditions than existing methods.

The rest of this paper is arranged as follows. Section 2 reviews the related literatures. Section 3 proposes our method for seeking the two-side M&A matching strategy from a perspective based on the mutual evaluation considering the herd behavior. Section 4 presents the results of the experiment with 51 banks. Section 5 summarizes this study.

2. Literature Review

2.1. DEA Cross Efficiency and Its Extensions

DEA [8] is a data-driven method for efficiency evaluation and usually used to evaluate the relative efficiency of a group of homogeneous DMUs. Based on the advantages of DEA that are mentioned in Section 1, DEA is widely used in various fields for efficiency evaluation, such as supply chains [25], forest [15], insurance industry [26], companies [27], and hotels [28].

In addition to the application of the DEA method, many scholars extend the classical CCR model [8] into other models that consider more factors. For example, Banker et al. [29] proposes the DEA model with variable returns to scale, which is later called the BBC model. Tone [30] considers the slacks of DMUs' inputs and outputs when improving the efficiencies and proposes the slack-based DEA model. Other studies can be found such as Toloo et al. [31], Guevel et al. [32], and Ghiyasi et al. [33]. In the classical DEA models including CCR and BCC models, the objective function is maximizing the efficiency of the evaluated DMU, so the evaluated DMU can select the optimal values of the indicator weights that maximize its efficiency. Thus, the efficiencies of DMUs are calculated based on their own indicator weights. To alleviate this shortcoming and obtain more fair evaluation, Sexton et al. [11] proposes the concept of the cross efficiency, where the final evaluation result is the average of self-evaluation and other-evaluation result values. The self-evaluation is based on the classical DEA model where the evaluated DMU can choose the indicator weights that are the most beneficial to itself. The other-evaluation results are the efficiencies

calculated by using other DMUs' optimal indicator weights. Based on such characteristics, the cross efficiency can provide a fairer evaluation result than the CCR and BCC models. Therefore, the cross-efficiency model is widely used in previous studies, such as Zhang et al. [12], Jin et al. [13], Yang et al. [14], and Wu et al. [15]. At the same time, we can obtain the self-evaluation and other-evaluation results of all DMUs. Therefore, in this study, we use the idea of the cross efficiency to measure the mutual evaluation of bidders and targets.

However, the previous studies on cross efficiency mostly ignore the herd behavior of decision makers. In reality, the opinion of one decision maker is easily influenced by others' opinions, especially the majority's opinions. Many researchers study the herd behavior from the perspectives of psychology and economics, such as Banerjee [16], Rook [17], and Ajraldi et al. [19]. As these studies mentioned, the herd behavior is ubiquitous because few decision makers are completely confident. Accordingly, when evaluating others' efficiencies, we need to consider the adjustment of DMUs' other-evaluation results based on the other-evaluation results of other DMUs.

2.2. Efficiency Evaluation of M&A

In previous studies, researchers use various methods to measure the potential gains of M&A activities from the efficiency evaluation perspective, where the DEA method is a popular method. For example, Lozano and Villa [34] construct DEA models to measure the potential gains of the merger from profit efficiency and cost efficiency perspectives. Wu et al. [20] use DEA to estimate the revenue efficiency of M&A between bank branches during multiple periods. Shi et al. [35] apply the cost efficiency to measure the potential gains of M&A considering that the new DMU after the merger will surpass the original production possibility set. In addition, Wu et al. [21] build a bi-level programming based on the DEA method in order to evaluate M&A performance of two-stage supply chains under the constraint resources. Li et al. [3] measure the merger efficiency based on the strong projection frontier. Al Tamimi et al. [22] propose a new directional distance function DEA model to evaluate the potential efficiency gains of banks' M&A. Recently, Hsu et al. [36] built a dynamic network DEA model to measure the performance of M&A among financial holding companies. Santín and Tejada [37] analyze the benefits of M&A between university departments based on the evaluation of efficiency gains by using the DEA method.

The above studies provide us with how to use the DEA method to evaluate M&A activities. However, they are post-evaluation based on the assumption that all M&A matchings are effective. In reality, this assumption does not necessarily hold true, as the failure rate of M&A is exceptionally high [3,7], and M&A matching is a key factor for M&A activities. In this study, based on the DEA method, we solve the M&A matching issue from the efficiency evaluation perspective.

2.3. Bounded Rationality in Partner Selection and Matching in M&A

A few scholars study the partner selection problem of M&A. For example, Zhu et al. [6] propose several DEA models to find the optimal partner for merger from the efficiency, cost, and revenue perspectives and the comprehensive view. In their study, the objective of the merger is maximizing the expansion of the efficiency, maximizing the revenue, or minimizing the cost of the new DMU after the merger, or all of them. Recently, Chang et al. [1] constructed a DEA-based Nash bargaining model to select the target of the merger. They set the profits of the acquirer and target companies as the disagreement point. Soltanifar et al. [38] propose a new inverse DEA model with a common set of weights to analyze M&A gains, which provide references to the decision maker in the selection of mergers. Gerami [39] provides two strategies for the alliance and partnership among DMUs and finds that the banks can obtain benefits from M&A in the semi-additive production

technology. Other related studies can be found in Lozano [40], Boamah and Amin [41], and others.

Furthermore, some studies provide methods for M&A matching. For example, Alam and Lee Ng [42] analyze the determinants of banks' M&A based on the bank-specific characteristics and country-specific characteristics of both parties. Ullah and Rashid [43] review the studies on M&A activities among Islamic and conventional banks from 2020 to 2022. Furthermore, a few scholars study M&A matching strategies from the perspective of efficiency evaluation. For example, Lin et al. [23] provide an M&A matching solution by maximizing the overall technical and scale efficiencies of the merger. The abovementioned studies provide various solutions for the partner selection and matching in M&A, most of which aim to maximize the overall performance of the merger but ignore the bidders' and targets' own satisfaction with each other. In order to form good M&A matching, we should simultaneously consider the bidders' and targets' satisfaction with each other rather than the overall performance or only one-side satisfaction.

Furthermore, the aforementioned studies mostly think the decision makers in M&A are completely rational. However, according to the research by Kahneman and Tversky [44] and Tversky and Kahneman [45], decision makers usually behave with bounded rationality when facing risk or uncertainty. In previous studies on M&A matching or partner selection, Shi and Wang [22] focus on the irrational behavior of decision makers and provide an M&A matching strategy based on the mutual evaluation where each DMU uses its own input–output indicator values as a reference point to evaluate the efficiency of other DMUs. Goursat [46] is a doctoral dissertation that studies the matching problems with limited information and bounded rationality. Furthermore, Liu et al. [47] integrate the prospect theory and cross-efficiency model, which inspires us to consider the bounded rationality of decision makers in performance evaluation. In addition, bidders and targets typically evaluate each other based on their own evaluation results. Therefore, our study takes the bounded rationality of bidders and targets into the M&A matching and sets the self-evaluation results as the reference points.

3. Our Proposed Two-Side M&A Matching Method

In this section, we first propose a novel mutual evaluation method considering the herd behavior, then construct a two-side matching model to seek the optimal M&A matching strategy considering the bounded rationality of bidders and targets from the efficiency evaluation perspective. This model possesses two objective functions that simultaneously maximize the bidders' and targets' satisfaction with each other.

3.1. Mutual Evaluation Considering Herd Behavior

As mentioned in Section 1, DEA has notable advantages compared with other efficiency evaluation approaches such as the analytic hierarchy process [9] and stochastic frontier analysis [10]. For example, DEA can evaluate DMUs with multiple input and output indicators in a comprehensive manner. In addition, as a non-parametric technique, DEA eliminates the need to specify a production function beforehand. Moreover, DEA determines indicator weights objectively through mathematical optimization, avoiding the subjectivity of expert scoring. Therefore, we select DEA as our theoretical foundation in this study. However, the traditional DEA model assigns each DMU its own preferred input and output weights, yielding only self-evaluation results. Consequently, it does not allow for the evaluation of other DMUs. To address this limitation, researchers have introduced the concept of cross efficiency, which incorporates both self-evaluation and peer evaluation. Specifically, the self-evaluation results of DMUs are obtained by running the traditional DEA model, where the optimal weights of inputs and outputs are beneficial for

the evaluated DMUs themselves. Then, as introduced in previous studies [11–15], each DMU use the optimal weights for themselves to evaluate the efficiencies of other DMUs. Such efficiencies are the other-evaluation results. Based on the ideas of the self-evaluation and other-evaluation results, in this study, we use the concept of cross efficiency in the DEA method to achieve the mutual evaluation between bidders and targets. Furthermore, as introduced before, humans or decision makers often observe others' opinions and adjust their original decision [48]. Similarly, when one DMU evaluates another DMU, it is often influenced by the assessments of other DMUs towards that DMU, particularly by the DMUs that the evaluating DMU trusts. Therefore, in this section, we propose a new approach of mutual evaluation considering the herd behavior of decision makers based on the DEA.

First, each DMU including bidders and targets evaluates its own efficiency by using the traditional DEA model and obtains its self-evaluation efficiencies. Let $X_j^B = \{x_{1j}^B, \dots, x_{ij}^B, \dots, x_{Ij}^B\}$ and $Y_j^B = \{y_{1j}^B, \dots, y_{rj}^B, \dots, y_{Rj}^B\}$ indicate the vectors of the inputs and outputs of bidders, respectively, and $X_n^T = \{x_{1n}^T, \dots, x_{in}^T, \dots, x_{In}^T\}$ and $Y_n^T = \{y_{1n}^T, \dots, y_{rn}^T, \dots, y_{Rn}^T\}$ be the vectors of the inputs and outputs of targets, respectively. We call the following BCC model [29] the self-evaluation DEA model and use it to calculate the self-evaluation results of all bidders and targets that are homogeneous. Here, we select the BCC model because the BCC model takes economies of scale into account, which is more feasible in practice than the CCR model [8].

$$\max \quad \theta_0 = \sum_{r=1}^R u_{r0} y_{r0} + \mu_0 \quad (1)$$

$$\text{s.t.} \quad \sum_{i=1}^I v_{i0} x_{i0} = 1 \quad (1a)$$

$$\sum_{r=1}^R u_{r0} y_{rj}^B - \sum_{i=1}^I v_{i0} x_{ij}^B + \mu_0 \leq 0; \quad j = 1, \dots, J \quad (1b)$$

$$\sum_{r=1}^R u_{r0} y_{rn}^T - \sum_{i=1}^I v_{i0} x_{in}^T + \mu_0 \leq 0; \quad n = 1, \dots, N \quad (1c)$$

$$v_{i0}, u_{r0} \geq 0; \quad i = 1, \dots, I; r = 1, \dots, R \quad (1d)$$

$$\mu_0 \text{ free} \quad (1e)$$

In this model, v_{i0} and u_{r0} are weights or important coefficients of the i th input and r th output of the evaluated DMU, respectively, where $i = 1, \dots, I$ and $r = 1, \dots, R$. Moreover, μ_0 is a free decision variable. Furthermore, x_{i0} indicates the i th input of the evaluated DMU, where $i = 1, \dots, I$, and y_{r0} indicates the r th output of the evaluated DMU, where $r = 1, \dots, R$. The subscript 0 belongs to the set of $(1, \dots, j, \dots, J) \cup (1, \dots, n, \dots, N)$, which means that the evaluated DMU may be the bidders or the targets. Based on this, we can obtain the self-evaluation results of all bidders and targets, including their efficiencies and weights of all inputs and outputs. Moreover, in this self-evaluation DEA model, each evaluated DMU will select the best values of the inputs' and outputs' weights in order to maximum its own efficiency. Based on this characteristic, the inputs' and outputs' weights from the self-evaluation indicate the bidders' and targets' preference of evaluation indicators. Therefore, each bidder and target will use these weights to evaluate others [11–15].

Next, we introduce the other-evaluation process without considering the herd behavior of decision makers, where each bidder or target uses its optimal weights or preference of inputs and outputs to evaluate other targets or bidders. When the evaluated DMU is the j th bidder, that is, $(x_{i0}, y_{r0}) = (x_{ij}^B, y_{rj}^B)$, we use $v_{ij}^B = v_{i0}^*$ and $u_{rj}^B = u_{r0}^*$ to be preference of this bidder for the i th input and r th output, where the asterisk means the optimal value of Model (1) and the superscript B indicates the bidder. We use $\theta_{jn}^{B \text{ of } T}$ to be the j th bidder's other-evaluation result of the n th target, where the superscript B of T indicates a bidder's

other-evaluation of a target and the subscripts j and n indicate the indexes of the bidder and target, respectively. The mathematical expression is as follows:

$$\theta_{jn}^{\text{B of T}} = \frac{\sum_{r=1}^R u_{rj}^{\text{B}} y_{rn}^{\text{T}} + \mu_j^{\text{B}}}{\sum_{i=1}^I v_{ij}^{\text{B}} x_{in}^{\text{T}}}; \quad j = 1, \dots, J; n = 1, \dots, N \quad (2a)$$

Similarly, when the evaluated DMU is the n th target, $(x_{i0}, y_{r0}) = (x_{in}^{\text{T}}, y_{rn}^{\text{T}})$, we use $v_{in}^{\text{T}} = v_{i0}^*$ and $u_{rn}^{\text{T}} = u_{r0}^*$ to be preference of this target for the i th input and r th output. Accordingly, the n th target's other-evaluation result of the j th bidder is as follows. The $\theta_{nj}^{\text{T of B}}$ in the left indicates the n th target's other-evaluation result of the j th bidder, where the superscript T of B means the target's other-evaluation of a bidder.

$$\theta_{nj}^{\text{T of B}} = \frac{\sum_{r=1}^R u_{rn}^{\text{T}} y_{rj}^{\text{B}} + \mu_n^{\text{T}}}{\sum_{i=1}^I v_{in}^{\text{T}} x_{ij}^{\text{B}}}; \quad j = 1, \dots, J; n = 1, \dots, N \quad (2b)$$

Based on Formulas (2a) and (2b), we can obtain the other-evaluation results of the bidders and targets, including the evaluation of each bidder of all targets, and the evaluation of each target of all bidders. These results can be viewed as the preliminary mutual evaluation results that have not been influenced by others.

Finally, each bidder or target adjust the other-evaluation results of the targets or bidders based on the opinions of others, particularly those of the trustee. In other words, we obtain the final mutual evaluation results through adjusting the other-evaluation results provided in Expressions (2a) and (2b) based on the consideration of the herd behavior. Before introducing the adjustment of bidders' other-evaluation results for targets, it is necessary to first identify whose influence shapes each bidder's other-evaluation of the target. In practice, decision makers usually influenced by the trusted ones. Taking the bidders' other-evaluation of targets as an example, for our focal bidder (e.g., B), if its other-evaluation result of another bidder (e.g., B') is higher than its own self-evaluation result, we can regard the latter (i.e., B') as the trusted bidder for the former (i.e., B). This is because decision makers usually often place their trust in those who they perceive to be superior to themselves. Here, we put all trusted bidders of B into the set Ω . Specifically, for a bidder B's other-evaluation result of another bidder B', we denote it as $\theta_{jj'}^{\text{B of B'}}$, where the subscript j and j' are the index of bidders and the superscripts B and B' indicate different bidders. The mathematical expression is as follows:

$$\theta_{jj'}^{\text{B of B'}} = \frac{\sum_{r=1}^R u_{rj}^{\text{B}} y_{rj'}^{\text{B'}} + \mu_j^{\text{B}}}{\sum_{i=1}^I v_{ij}^{\text{B}} x_{ij'}^{\text{B'}}}; \quad j = 1, \dots, J; j' = 1, \dots, J; j' \neq j \quad (3)$$

Furthermore, in terms of the degree of trust, we measure B's level of trust in B' by the extent to which B's other-evaluation result of B' exceeds B's self-evaluation result. We use $\theta_j^{\text{B}} = \theta_0^*$ to be the self-evaluation results of bidders, where the * indicates the optimal solution of Model (1) when $(x_{i0}, y_{r0}) = (x_{ij}^{\text{B}}, y_{rj}^{\text{B}})$. Then, we can obtain B's level of trust in B' by using the following expression, where the level of trust is zero when the bidder B thinks it is better than the bidder B':

$$\text{TG}_{jj'}^{\text{B of B'}} = \begin{cases} \frac{\theta_{jj'}^{\text{B of B'}} - \theta_j^{\text{B}}}{\theta_j^{\text{B}}}, & \text{if } \theta_{jj'}^{\text{B of B'}} \geq \theta_j^{\text{B}}, j = 1, \dots, J; j' = 1, \dots, J \\ 0, & \text{if } \theta_{jj'}^{\text{B of B'}} < \theta_j^{\text{B}}, j = 1, \dots, J; j' = 1, \dots, J \end{cases} \quad (4)$$

Moreover, let k to be the herd coefficient, which indicates the extent to which a decision maker believes in the opinions of others, or in other words, the degree of self-doubt. Therefore, taking the herd behavior into the mutual evaluation, the bidders' other-evaluation results of targets shown in Expression (2a) should be adjusted as follows. The expression $\sum_{j' \in \Omega} (\mathbb{T}G_{jj'}^{\text{BofB}'} \times \theta_{jn}^{\text{B'ofT}})$ means the weighted sum of the other-evaluation results of the trusted DMUs regarding the same target.

$$\hat{\theta}_{jn}^{\text{BofT}} = (1 - k) \times \theta_j^{\text{B}} + k \times \sum_{j' \in \Omega} (\mathbb{T}G_{jj'}^{\text{B of B}'} \times \theta_{jn}^{\text{B'of T}}); j = 1, \dots, J; n = 1, \dots, N \quad (5)$$

Similarly, we can obtain the targets' adjusted other-evaluation results of bidders. For a target T 's other-evaluation result of another bidder T' , we denote it as $\theta_{nn'}^{\text{T of T}'}$, where the subscript n and n' are the index of targets and both the superscript T and T' indicate targets. Its mathematical expression is as follows:

$$\theta_{nn'}^{\text{T of T}'} = \frac{\sum_{r=1}^R u_{rn}^{\text{T}} y_{rn'}^{\text{T}'} + \mu_n^{\text{T}}}{\sum_{i=1}^I v_{in}^{\text{T}} x_{in'}^{\text{T}'}}; \quad n = 1, \dots, N; n' = 1, \dots, N \quad (6)$$

Accordingly, T 's level of trust in T' can be measured by using the following expression, where θ_j^{T} is the self-evaluation result of the target T . Furthermore, T 's level of trust in T' who are weaker than itself is zero.

$$\mathbb{T}G_{nn'}^{\text{T of T}'} = \begin{cases} \frac{\theta_{nn'}^{\text{T of T}'} - \theta_n^{\text{T}}}{\theta_n^{\text{T}}}, & \text{if } \theta_{nn'}^{\text{T of T}'} \geq \theta_n^{\text{T}}, \quad n = 1, \dots, N; n' = 1, \dots, N \\ 0, & \text{if } \theta_{nn'}^{\text{T of T}'} < \theta_n^{\text{T}}, \quad n = 1, \dots, N; n' = 1, \dots, N \end{cases} \quad (7)$$

Based on the analysis of trusted DMUs and the specific level of trust, we can adjust the target T 's other-evaluation result of the bidder B by using the following expression:

$$\hat{\theta}_{nj}^{\text{TofB}} = (1 - k) \times \theta_j^{\text{T}} + k \times \sum_{j' \in \Omega} (\mathbb{T}G_{nn'}^{\text{T of T}'} \times \theta_{nj'}^{\text{T'of B}}); j = 1, \dots, J; n = 1, \dots, N \quad (8)$$

3.2. Matching Model Considering the Bounded Rationality of Bidders and Targets

After obtaining the evaluation between bidders and targets towards each other, next we seek the optimal M&A matching strategy based on the two-side matching theory. Furthermore, in the M&A activities, decision makers cannot make accurate judgments about future development, so we can think that M&A activities are often full of uncertainties. In this case, decision makers tend to behave in a bounded rational or not completely rational manner [22]. Based on this, we take the bounded rationality of bidders and targets into account when seeking the M&A matching strategy and propose a new matching model below.

Before introducing the matching model, we first introduce how to measure the bidders' and targets' satisfaction with each other when considering their bounded rationality. According to the prospect theory developed by Kahneman and Tversky [44], decision makers usually think the utility of each prospect is based on the deviation from the reference point, not only the final state, and we can use the following formula to evaluate the prospect when considering the bounded rationality of decision makers. The notation Δ indicates the difference between the possible state from the reference point, and $U, w, v(\Delta)$ is, respectively, the total utility, decision weight of each possible state, and prospect value function.

$$U = \sum w v(\Delta) \quad (9)$$

When $\Delta \geq 0$, the decision makers feel the gain, and for this state, $v(\Delta) = \Delta \phi^\alpha$ expect that $v(0) = 0$; otherwise, they feel the loss, and now $v(\Delta) = -\mu |\Delta \phi|^\beta$. Furthermore,

the parameters $\alpha, \beta \in (0, 1)$, respectively, represent the bump degree of the gain and loss regions of the prospect value function; μ reflects the loss aversion; and the value is greater than 1. In addition, for the decision weight of each possible state w , Kahneman and Tversky [44] and Tversky and Kahneman [45] find that it is a two-part power function of the possibility of each prospect and provide the following formula to depict it. The parameters γ and δ are attitude coefficients of decision makers for the gain and loss, respectively.

$$w(p) = \begin{cases} \frac{p^\gamma}{[p^\gamma + (1-p)^\gamma]^{\frac{1}{\gamma}}} & \Delta \geq 0 \\ \frac{p^\delta}{[p^\delta + (1-p)^\delta]^{\frac{1}{\delta}}} & \Delta < 0 \end{cases} \quad (10)$$

Therefore, the total utility U is as follows, which can be used to measure the bidders' and targets' satisfaction with each other in our study:

$$U = \sum w v(\Delta) = \begin{cases} \frac{p^\gamma}{[p^\gamma + (1-p)^\gamma]^{\frac{1}{\gamma}}} \Delta^\alpha, & \Delta \geq 0 \\ -\frac{p^\delta}{[p^\delta + (1-p)^\delta]^{\frac{1}{\delta}}} \mu |\Delta|^\beta, & \Delta < 0 \end{cases} \quad (11)$$

The reference point will affect the value of U . In this study, based on the mutual evaluation, we can define the bidders' satisfaction for targets based on the difference between the self-evaluation and other-evaluation result, and the same for the targets'. Accordingly, we set the self-evaluation results of the bidders and targets as the reference points. Therefore, we use $\Delta = \hat{\theta}_{jn}^{\text{BoFT}} - \theta_j^{\text{B}}$ and $\Delta = \hat{\theta}_{nj}^{\text{ToFB}} - \theta_n^{\text{T}}$ to calculate the prospect value of bidders and targets, respectively. Here, the $\hat{\theta}_{jn}^{\text{BoFT}}$ and $\hat{\theta}_{nj}^{\text{ToFB}}$ are the adjusted other-evaluation results calculated by (5) and (8).

Then, with the purpose of maximizing the utilities of two-side parties, we construct the following matching model considering the bounded rationality of bidders and targets, where U_{jn}^{BoFT} and U_{nj}^{ToFB} indicate the j th bidders' utility of the n th targets and the n th target's utility of the j th bidder, respectively.

$$\max Z_1 = \sum_{j=1}^J \sum_{n=1}^N U_{jn}^{\text{BoFT}} \tau_{jn} \quad (12a)$$

$$\max Z_2 = \sum_{n=1}^N \sum_{j=1}^J U_{nj}^{\text{ToFB}} \tau_{jn} \quad (12b)$$

$$\text{s.t. } \sum_{j=1}^J \tau_{jn} \leq 1; \quad n = 1, \dots, N \quad (12c)$$

$$\sum_{n=1}^N \tau_{jn} \leq 1; \quad j = 1, \dots, J \quad (12d)$$

$$\tau_{jn} = (0, 1); \quad j = 1, \dots, J; n = 1, \dots, N \quad (12e)$$

In Model (12a)–(12e), τ_{jn} is a binary variable, where $j = 1, \dots, J$ and $n = 1, \dots, N$. $\tau_{jn} = 1$ indicates that the j th bidder match with the n th target, and $\tau_{jn} = 0$ means they do not match. In this study, we focus on the one-to-one matching between the bidders and targets, which means that any one bidder (or target) can only match with one target (or bidder), as shown in the constraints in Model (12a)–(12e). However, some bidders or targets may have no matching targets or bidders, because $\tau_{jn} = 0$ is possible. In fact, by altering the values on the right-hand side of constraints (12c) or (12d) to other integers, we can investigate one-to-many or many-to-one matchings between bidders and targets. Furthermore, our purpose is seeking the match strategy with the maximum bidders' and the targets' satisfaction degree with each other simultaneously. Therefore, we set two objective functions, where the satisfaction degree is based on the sum of the utility.

3.3. Solution of the Matching Model

To find the optimal solutions of Model (12a)–(12e), we use a method based on the membership function to transform the two objective functions into one objective. First, we construct two models where the objective functions are Formulae (12a) and (12b), respectively, and the constraints are the same with Formulae (12c) and (12d). Based on this, we obtain the maximum value of Z_1 and Z_2 , denoted Z_1^{max} and Z_2^{max} . Similarly, we calculate the minimum value of Z_1 and Z_2 with the same constraints with the Formulae (12c) and (12d), marked Z_1^{min} and Z_2^{min} . Second, we build Model (13) based on the weighted sum of the membership functions of two objective functions in Model (12a)–(12e), as follows. In Model (13), w_1 and w_2 are the weights of two objectives Z_1 and Z_2 , and $\xi_{Z1} = 1 - \frac{Z_1^{max} - Z_1}{Z_1^{max} - Z_1^{min}}$ and $\xi_{Z2} = 1 - \frac{Z_2^{max} - Z_2}{Z_2^{max} - Z_2^{min}}$ denote the membership functions of Z_1 and Z_2 , respectively. In addition, in this study, we focus on seeking a two-side M&A matching strategy that can maximize the bidders' and targets' satisfaction with each other simultaneously, so we set $w_1 = w_2 = 1/2$.

$$\max w_1 \xi_{Z1} + w_2 \xi_{Z2} \quad (13)$$

$$\text{s.t. } \sum_{j=1}^J \tau_{jn} \leq 1; \quad n = 1, \dots, N \quad (13a)$$

$$\sum_{n=1}^N \tau_{jn} \leq 1; \quad j = 1, \dots, J \quad (13b)$$

$$\tau_{jn} = (0, 1); \quad n = 1, \dots, N; j = 1, \dots, J \quad (13c)$$

4. Application of Our Proposed Method

To illustrate our method, in this section, we construct an experiment based on the data of 51 banks. In addition, we make sensitivity analysis to show the results of our method under different parameter settings. Also, based on the results of experiment, we present the discussion of our proposed two-side M&A matching method.

4.1. Data and Experiment

In this section, we apply our method into the two-side M&A matching of 51 banks, where each bank is a DMU in our study. In addition, we select 25 banks as the targets and the other 26 banks as the bidders. The data are from Boamah and Amin [41], where the inputs of these banks are interest expenses (i.e., x_{1j}^T and x_{1j}^B), labor costs (i.e., x_{2j}^T and x_{2j}^B), and costs of equipment and premises (i.e., x_{3j}^T and x_{3j}^B). Also, the outputs are balances with other banks (i.e., y_{1j}^T and y_{1j}^B), securities (i.e., y_{2j}^T and y_{2j}^B), and loans (i.e., y_{3j}^T and y_{3j}^B). We present all data in Table 1.

Table 1. Inputs and outputs of banks from Boamah and Amin [41].

Targets	x_{1j}^T	x_{2j}^T	x_{3j}^T	y_{1j}^T	y_{2j}^T	y_{3j}^T
DMU 1	12,030,000	26,053,000	6,574,000	321,590,000	260,071,000	874,492,000
DMU 2	6,797,000	17,438,000	4,667,000	159,983,000	418,582,000	930,337,000
DMU 3	9,433,000	24,857,000	4,847,000	171,910,000	399,795,000	922,214,000
DMU 4	13,486,000	14,843,000	1,821,000	179,696,000	323,535,000	642,173,000
DMU 5	2,906,278	7,143,995	1,049,107	21,369,509	111,246,751	284,800,984
DMU 6	2,694,444	5,251,503	1,299,328	16,477,644	83,180,647	224,541,765
DMU 7	2,674,738	5,599,066	1,238,290	63,273,007	66,710,323	145,275,378
DMU 8	2,254,869	2,391,864	724,736	12,493,366	118,413,161	147,169,695
DMU 9	1,822,000	3,902,000	734,000	84,268,000	116,053,000	26,039,000
DMU 10	716,282	4,392,756	1,609,084	75,992,027	86,823,543	25,850,933
DMU 11	1,130,000	3,824,000	732,000	3,611,000	45,833,000	143,259,000
DMU 12	1,021,835	2,834,754	531,510	5,759,223	31,414,275	151,773,966
DMU 13	3,065,000	408,000	49,000	30,522,000	2,936,000	75,981,000

Table 1. Cont.

Targets	x_{1j}^T	x_{2j}^T	x_{3j}^T	y_{1j}^T	y_{2j}^T	y_{3j}^T
DMU 14	2,134,927	827,474	195,004	16,895,877	46,229,666	66,651,806
DMU 15	2,355,000	969,000	57,000	4,091,000	22,558,000	120,065,000
DMU 16	874,000	75,000	17,000	14,999,000	56,740,000	57,972,000
DMU 17	833,984	2,132,425	415,034	4,510,217	32,304,735	94,709,936
DMU 18	806,063	2,007,746	396,230	3,295,262	30,936,413	90,940,461
DMU 19	693,721	2,044,429	304,313	38,913,888	51,197,684	32,377,459
DMU 20	826,942	2,392,684	342,382	8,213,749	26,942,302	85,234,124
DMU 21	1,004,168	1,617,353	493,556	4,318,567	12,979,263	98,699,167
DMU 22	478,939	1,880,615	463,911	3,467,026	24,619,079	82,616,342
DMU 23	860,888	1,406,981	332,788	13,690,820	17,973,105	80,161,870
DMU 24	2,767,499	196,097	177,247	2,958,018	15,679,177	95,246,115
DMU 25	489,153	1,633,131	286,837	9,641,162	12,068,166	87,281,714
Bidders	x_{1j}^B	x_{2j}^B	x_{3j}^B	y_{1j}^B	y_{2j}^B	y_{3j}^B
DMU 26	1,948,393	74,089	22,392	20,452,309	1,955,074	91,694,824
DMU 27	654,536	1,437,922	323,041	2,592,121	22,348,994	74,874,375
DMU 28	1,962,672	1,058,471	52,803	14,811,896	3,475,449	87,459,200
DMU 29	530,498	1,122,359	200,962	2,811,159	16,234,808	75,525,219
DMU 30	648,660	1,040,482	223,393	3,097,780	13,634,835	64,370,078
DMU 31	688,114	1,088,034	240,598	4,488,941	12,960,589	61,953,747
DMU 32	455,204	917,125	360,462	4,381,225	13,006,251	51,152,423
DMU 33	413,000	138,000	27,000	7,223,000	12,503,000	54,765,000
DMU 34	250,928	967,129	184,088	4,514,874	12,087,410	49,495,150
DMU 35	250,398	1,070,095	221,349	1,231,922	15,511,046	46,312,248
DMU 36	43,884	689,880	63,640	3,408,468	23,077,746	28,057,377
DMU 37	99,028	787,196	157,252	2,658,890	9,934,276	35,463,205
DMU 38	410,010	307,404	48,832	432,784	9,032,345	36,678,427
DMU 39	557,418	475,005	47,617	1,412,929	5,967,721	27,828,008
DMU 40	258,707	375,189	69,824	3,282,377	2,773,056	32,144,142
DMU 41	294,276	641,672	123,855	2,055,884	4,649,921	28,034,702
DMU 42	183,000	182,000	28,000	17,588,000	5000	10,210,000
DMU 43	31,972	645,894	154,809	1,131,893	6,735,308	25,346,591
DMU 44	233,451	514,566	91,005	1,256,897	9,114,602	18,637,162
DMU 45	268,688	482,676	82,363	729,617	6,689,021	22,781,670
DMU 46	519,103	359,248	44,772	5,514,050	100,813	25,840,618
DMU 47	219,180	349,895	110,539	493,838	6,595,405	21,974,970
DMU 48	171,946	418,399	128,227	1,118,529	3,994,800	25,734,653
DMU 49	85,186	433,798	111,751	3,317,919	12,450,688	13,967,601
DMU 50	378,901	225,266	70,767	382,072	8,106,359	21,904,069
DMU 51	291,019	333,816	108,763	428,629	3,817,790	24,918,765

Based on these data, we apply our proposed method into banks' M&A following with the processes shown in Figure 1. The pink boxes represent each step, with the blue text in brackets indicating the model or formula involved in that step. The circles denote the input and output data for each step.

First, by running Model (1) with the data in Table 1, we obtain the self-evaluation results of all DMUs including 25 bidders and 26 targets. This result is presented in Table 2, where T indicates the target and B represents the bidder. From this result, we can see that the targets 10 and 16 are efficient under the self-evaluation situation, and the bidders 1, 8, 11, 17, 18, and 24 are efficient under the self-evaluation situation.

Then, based on the concept of the cross efficiency in the DEA field, we obtain each bidder's preliminary other-evaluation results of all targets, and each target's preliminary other-evaluation results. Owing to the space limitation, here we just take the targets' other-evaluation of bidders as an example to illustrate our method. First, we present the target's preliminary other-evaluation results of bidders in Table 3 and each target's other-evaluation results of other targets in Table 4.

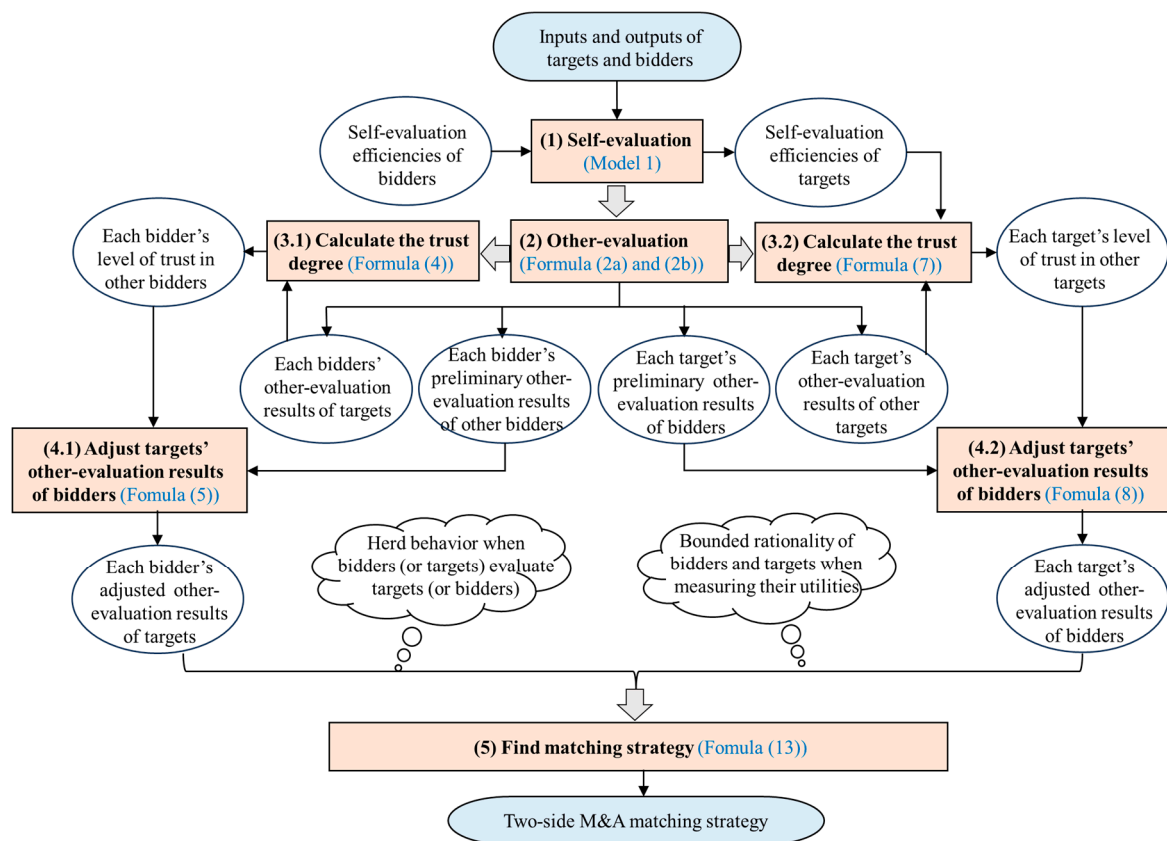


Figure 1. Experiment process.

Table 2. Self-evaluation results of bidders and targets.

Self-Evaluation Results of Targets				Self-Evaluation Results of Bidders			
T 1	0.48	T 14	0.36	B 1	1.00	B 14	0.56
T 2	0.70	T 15	0.70	B 2	0.59	B 15	0.86
T 3	0.50	T 16	1.00	B 3	0.58	B 16	0.59
T 4	0.39	T 17	0.55	B 4	0.74	B 17	1.00
T 5	0.48	T 18	0.55	B 5	0.57	B 18	1.00
T 6	0.45	T 19	0.77	B 6	0.52	B 19	0.66
T 7	0.39	T 20	0.47	B 7	0.60	B 20	0.66
T 8	0.60	T 21	0.56	B 8	1.00	B 21	0.60
T 9	0.77	T 22	0.69	B 9	0.79	B 22	0.84
T 10	1.00	T 23	0.56	B 10	0.70	B 23	0.92
T 11	0.54	T 24	0.57	B 11	1.00	B 24	1.00
T 12	0.70	T 25	0.77	B 12	0.93	B 25	0.76
T 13	0.70			B 13	0.71	B 26	0.75

Next, to identify the trusted targets of each target, we compare each target's self-evaluation results and other-evaluation results of other targets. Also, we use Formula (7) to calculate each target's level of trust in other targets, which are shown in Table 5. Subsequently, let the herd coefficient $k = 0.3$ and we obtain targets' adjusted other-evaluation results of bidders by using Formula (8), as shown in Table 6. Taking target 9 as an example, its self-evaluation result is 0.77, which is smaller than its other-evaluation results of targets 10 and 16 and higher than others. Therefore, target 9 trusts targets 10 and 16, and the trust degrees are 0.11 and 0.30, respectively. Accordingly, target 9 adjusts its other-evaluation results of bidders; for example, target 9's other-evaluation result of 0.16 for bidder 1 is changed to 0.13. Furthermore, for targets 10 and 16, they are efficient under

the self-evaluation situation, so they do not trust any targets. Accordingly, target 10's and 16's preliminary other-evaluation results are the same with their adjusted other-evaluation results of bidders.

Finally, based on the mutual evaluation results, we run Model (13) to seek the optimal matching strategy considering the bounded rationality of bidders and targets. According to the conclusion provided by Tversky and Kahneman [42], the parameters in Formula (11) are $\alpha = 0.89$, $\beta = 0.92$, $\mu = 2.25$, $\gamma = 0.61$, and $\delta = 0.69$. Table 7 presents the matching result. We can see that the matching pairs include T 24-B 1, T 12-B 2, T 15-B 3, T 5-B 4, T 22-B 5, T 25-B 6, T 2-B 7, T 4-B 8, T 3-B 9, T 11-B 10, T 14-B 11, T 1-B 12, T 21-B 13, T 23-B 15, T 18-B 16, T 7-B 17, T 6-B 18, T 16-B 19, T 20-B 20, T 8-B 24, and T 17-B 26. In addition, the targets 9, 10, 13, and 19 are not matched with any one bidder, and the bidders 14, 21, 22, 23, and 25 are not matched with any one target. This is because in our matching model, the binary variable τ_{jn} may be equal to zero. When $\tau_{jn} = 0$ holds for all $j = 1, \dots, J$ or all $n = 1, \dots, N$, the target n or the bidder j is not matched. Also, in practice, to select the optimal M&A partner or achieve the stability, in the two-side matching, some bidders or targets are not matched with others. An unmatched target in a matching model does not imply it is “bad” or “unattractive.” Rather, it reflects a misalignment between preferences, constraints, and strategic fit. Moreover, in this study, we focus on the one-to-one match of bidders and targets, and the number of bidders is more than the number of targets. Furthermore, if we study the one-to-many or many-to-one match of bidders and targets, we only need to change the value in the right of the constraint (12c) or (12d).

4.2. Sensitivity Analysis

In Section 4.1, we showed the adjusted other-evaluation results and the matching results in the situation where the herd coefficient $k = 0.3$ and the risk parameters in Formula (11) are $\alpha = 0.89$, $\beta = 0.92$, and $\mu = 2.25$. To further illustrate our method, in this section, we present the sensitivity analysis.

First, we present the adjusted other-evaluation results under three representative values of the herd coefficient; they are $k = 0.7$, $k = 0.5$, and $k = 0$, as shown in Appendix A. In Section 4.1, $k = 0.3$ represents the situation where targets and bidders are relatively high self-confidence while still being somewhat influenced by trusted individuals. In contrast, $k = 0.7$ reflects the opposite case, where the targets and bidders show low self-confidence and place greater reliance on the opinions of those they trust. Furthermore, $k = 0.5$ indicates a relatively neutral state, and $k = 0$ signifies that the targets and bidders are entirely confident. The situation with $k = 0$ is equal to the situation without considering the herd behavior in the mutual evaluation. Second, with the above representative values of the herd coefficient, we obtain different matching results, which are presented in Appendix B. At the same time, we report the overall utility of these matching results, which are the optimal values of Model (13). The following figure (i.e., Figure 2) reveals that the higher the herd coefficient, the greater the overall utility. Such a result tells us that during M&A, mutual evaluations considering others' opinions can enhance overall satisfaction with the restructuring process.

Second, we analyze the matching results under different parameter values in the calculation of the utility. In other words, different risk attitudes of decision makers generate different matching results when the herd coefficient keeps the value $k = 0.3$. Inspired by Liu et al. [47], we set $\alpha = 0.5$, $\beta = 0.3$, and $\mu = 3$. The matching result is shown in Appendix C. These results tell us we can seek specific two-side M&A matching strategies according to the risk attitude of decision makers in practice.

Table 3. Target’s preliminary other-evaluation results of bidders.

	B 1	B 2	B 3	B 4	B 5	B 6	B 7	B 8	B 9	B 10	B 11	B 12	B 13	B 14	B 15	B 16	B 17	B 18	B 19	B 20	B 21	B 22	B 23	B 24	B 25	B 26
T 1	0.42	0.53	0.33	0.67	0.52	0.49	0.57	1.00	0.76	0.63	1.00	0.88	0.53	0.42	0.53	0.33	0.67	0.52	0.49	0.57	1.00	0.76	0.63	1.00	0.88	0.53
T 2	0.42	0.53	0.33	0.67	0.52	0.49	0.57	1.00	0.76	0.63	1.00	0.88	0.53	0.42	0.53	0.33	0.67	0.52	0.49	0.57	1.00	0.76	0.63	1.00	0.88	0.53
T 3	0.42	0.53	0.33	0.67	0.52	0.49	0.57	1.00	0.76	0.63	1.00	0.88	0.53	0.42	0.53	0.33	0.67	0.52	0.49	0.57	1.00	0.76	0.63	1.00	0.88	0.53
T 4	0.38	0.46	0.28	0.54	0.43	0.41	0.49	1.00	0.59	0.51	1.00	0.64	0.49	0.38	0.46	0.28	0.54	0.43	0.41	0.49	1.00	0.59	0.51	1.00	0.64	0.49
T 5	0.38	0.59	0.32	0.74	0.57	0.52	0.59	1.00	0.79	0.70	1.00	0.93	0.61	0.38	0.59	0.32	0.74	0.57	0.52	0.59	1.00	0.79	0.70	1.00	0.93	0.61
T 6	0.38	0.59	0.32	0.74	0.57	0.52	0.60	1.00	0.79	0.70	1.00	0.93	0.61	0.38	0.59	0.32	0.74	0.57	0.52	0.60	1.00	0.79	0.70	1.00	0.93	0.61
T 7	0.38	0.46	0.28	0.54	0.43	0.41	0.49	1.00	0.59	0.51	1.00	0.64	0.49	0.38	0.46	0.28	0.54	0.43	0.41	0.49	1.00	0.59	0.51	1.00	0.64	0.49
T 8	0.32	0.51	0.25	0.59	0.47	0.43	0.50	1.00	0.59	0.57	1.00	0.65	0.58	0.32	0.51	0.25	0.59	0.47	0.43	0.50	1.00	0.59	0.57	1.00	0.65	0.58
T 9	0.16	0.25	0.11	0.24	0.19	0.20	0.27	0.55	0.33	0.30	1.00	0.37	0.21	0.16	0.25	0.11	0.24	0.19	0.20	0.27	0.55	0.33	0.30	1.00	0.37	0.21
T 10	0.12	0.12	0.09	0.13	0.10	0.11	0.16	0.28	0.26	0.17	1.00	0.35	0.07	0.12	0.12	0.09	0.13	0.10	0.11	0.16	0.28	0.26	0.17	1.00	0.35	0.07
T 11	0.38	0.59	0.32	0.74	0.57	0.52	0.59	1.00	0.79	0.70	1.00	0.93	0.61	0.38	0.59	0.32	0.74	0.57	0.52	0.59	1.00	0.79	0.70	1.00	0.93	0.61
T 12	0.38	0.59	0.32	0.74	0.57	0.52	0.59	1.00	0.79	0.70	1.00	0.93	0.61	0.38	0.59	0.32	0.74	0.57	0.52	0.59	1.00	0.79	0.70	1.00	0.93	0.61
T 13	1.00	0.01	0.32	0.02	0.02	0.02	0.01	0.31	0.03	0.01	0.06	0.02	0.01	1.00	0.01	0.32	0.02	0.02	0.02	0.01	0.31	0.03	0.01	0.06	0.02	0.01
T 14	0.38	0.46	0.28	0.54	0.43	0.41	0.49	1.00	0.59	0.51	1.00	0.64	0.49	0.38	0.46	0.28	0.54	0.43	0.41	0.49	1.00	0.59	0.51	1.00	0.64	0.49
T 15	0.86	0.15	0.58	0.24	0.19	0.17	0.10	1.00	0.18	0.14	0.30	0.15	0.43	0.86	0.15	0.58	0.24	0.19	0.17	0.10	1.00	0.18	0.14	0.30	0.15	0.43
T 16	0.02	0.27	0.02	0.25	0.19	0.17	0.23	0.42	0.27	0.33	1.00	0.34	0.26	0.02	0.27	0.02	0.25	0.19	0.17	0.23	0.42	0.27	0.33	1.00	0.34	0.26
T 17	0.38	0.59	0.32	0.74	0.57	0.52	0.60	1.00	0.79	0.70	1.00	0.93	0.61	0.38	0.59	0.32	0.74	0.57	0.52	0.60	1.00	0.79	0.70	1.00	0.93	0.61
T 18	0.38	0.59	0.32	0.74	0.57	0.52	0.60	1.00	0.79	0.70	1.00	0.93	0.61	0.38	0.59	0.32	0.74	0.57	0.52	0.60	1.00	0.79	0.70	1.00	0.93	0.61
T 19	0.16	0.25	0.11	0.24	0.19	0.20	0.27	0.55	0.33	0.30	1.00	0.37	0.21	0.16	0.25	0.11	0.24	0.19	0.20	0.27	0.55	0.33	0.30	1.00	0.37	0.21
T 20	0.38	0.59	0.32	0.74	0.57	0.52	0.59	1.00	0.79	0.70	1.00	0.93	0.61	0.38	0.59	0.32	0.74	0.57	0.52	0.59	1.00	0.79	0.70	1.00	0.93	0.61
T 21	0.38	0.59	0.32	0.74	0.57	0.52	0.60	1.00	0.79	0.70	0.99	0.93	0.61	0.38	0.59	0.32	0.74	0.57	0.52	0.60	1.00	0.79	0.70	0.99	0.93	0.61
T 22	0.38	0.59	0.32	0.74	0.57	0.52	0.60	1.00	0.79	0.70	1.00	0.93	0.61	0.38	0.59	0.32	0.74	0.57	0.52	0.60	1.00	0.79	0.70	1.00	0.93	0.61
T 23	0.42	0.53	0.33	0.67	0.52	0.49	0.57	1.00	0.76	0.63	1.00	0.88	0.53	0.42	0.53	0.33	0.67	0.52	0.49	0.57	1.00	0.76	0.63	1.00	0.88	0.53
T 24	1.00	0.12	0.18	0.16	0.15	0.13	0.13	0.80	0.12	0.11	0.10	0.11	0.27	1.00	0.12	0.18	0.16	0.15	0.13	0.13	0.80	0.12	0.11	0.10	0.11	0.27
T 25	0.39	0.58	0.32	0.74	0.56	0.52	0.60	1.00	0.79	0.70	1.00	0.93	0.60	0.39	0.58	0.32	0.74	0.56	0.52	0.60	1.00	0.79	0.70	1.00	0.93	0.60

Table 4. Target’s other-evaluation results of other targets.

	T 1	T 2	T 3	T 4	T 5	T 6	T 7	T 8	T 9	T 10	T 11	T 12	T 13	T 14	T 15	T 16	T 17	T 18	T 19	T 20	T 21	T 22	T 23	T 24	T 25
T 1	0.48	0.70	0.50	0.35	0.46	0.42	0.38	0.40	0.33	0.46	0.48	0.63	0.26	0.26	0.34	0.61	0.50	0.50	0.47	0.46	0.51	0.62	0.56	0.25	0.76
T 2	0.48	0.70	0.50	0.35	0.46	0.42	0.38	0.40	0.33	0.46	0.48	0.63	0.26	0.26	0.34	0.61	0.50	0.50	0.47	0.46	0.51	0.62	0.56	0.25	0.76
T 3	0.48	0.70	0.50	0.35	0.46	0.42	0.38	0.40	0.33	0.46	0.48	0.63	0.26	0.26	0.34	0.61	0.50	0.50	0.47	0.46	0.51	0.62	0.56	0.25	0.76
T 4	0.44	0.68	0.48	0.39	0.42	0.40	0.39	0.54	0.55	0.61	0.40	0.48	0.25	0.36	0.31	1.00	0.44	0.44	0.62	0.39	0.39	0.50	0.49	0.23	0.55
T 5	0.38	0.66	0.47	0.30	0.48	0.45	0.28	0.42	0.07	0.11	0.54	0.70	0.20	0.23	0.38	0.53	0.55	0.55	0.21	0.47	0.56	0.68	0.53	0.28	0.77
T 6	0.38	0.66	0.47	0.30	0.48	0.45	0.29	0.42	0.08	0.12	0.54	0.69	0.20	0.23	0.38	0.54	0.55	0.55	0.22	0.47	0.56	0.69	0.53	0.28	0.77
T 7	0.44	0.68	0.48	0.39	0.42	0.40	0.39	0.54	0.55	0.61	0.40	0.48	0.25	0.36	0.31	1.00	0.44	0.44	0.62	0.39	0.39	0.50	0.49	0.23	0.55
T 8	0.32	0.64	0.44	0.35	0.45	0.42	0.29	0.60	0.32	0.32	0.45	0.53	0.16	0.34	0.36	1.00	0.48	0.49	0.39	0.40	0.43	0.54	0.44	0.27	0.52
T 9	0.34	0.53	0.37	0.33	0.28	0.26	0.35	0.50	0.77	0.86	0.22	0.21	0.15	0.33	0.12	1.00	0.27	0.26	0.77	0.25	0.13	0.28	0.29	0.08	0.25
T 10	0.31	0.37	0.27	0.20	0.16	0.14	0.29	0.20	0.60	1.00	0.12	0.12	0.11	0.15	0.05	0.39	0.14	0.13	0.67	0.17	0.08	0.17	0.21	0.03	0.23
T 11	0.38	0.66	0.47	0.30	0.48	0.45	0.28	0.42	0.07	0.11	0.54	0.70	0.20	0.23	0.38	0.53	0.55	0.55	0.21	0.47	0.56	0.68	0.53	0.28	0.77
T 12	0.38	0.66	0.47	0.30	0.48	0.45	0.28	0.42	0.07	0.11	0.54	0.70	0.20	0.23	0.38	0.53	0.55	0.55	0.21	0.47	0.56	0.68	0.53	0.28	0.77

	T 1	T 2	T 3	T 4	T 5	T 6	T 7	T 8	T 9	T 10	T 11	T 12	T 13	T 14	T 15	T 16	T 17	T 18	T 19	T 20	T 21	T 22	T 23	T 24	T 25
T 13	0.06	0.04	0.04	0.12	0.02	0.02	0.06	0.02	0.14	0.06	0.01	0.01	0.70	0.10	0.08	1.00	0.01	0.01	0.15	0.03	0.01	0.01	0.05	0.02	0.04
T 14	0.44	0.68	0.48	0.39	0.42	0.40	0.39	0.54	0.55	0.61	0.40	0.48	0.25	0.36	0.31	1.00	0.44	0.44	0.62	0.39	0.39	0.50	0.49	0.23	0.55
T 15	0.09	0.13	0.13	0.20	0.18	0.11	0.08	0.13	0.02	0.01	0.13	0.19	0.40	0.18	0.70	1.00	0.15	0.15	0.07	0.16	0.13	0.12	0.16	0.26	0.20
T 16	0.17	0.45	0.30	0.25	0.28	0.26	0.20	0.56	0.51	0.50	0.25	0.21	0.01	0.29	0.13	1.00	0.28	0.28	0.49	0.22	0.12	0.29	0.19	0.09	0.15
T 17	0.38	0.66	0.47	0.30	0.48	0.45	0.29	0.42	0.08	0.12	0.54	0.69	0.20	0.23	0.38	0.54	0.55	0.55	0.22	0.47	0.56	0.69	0.53	0.28	0.77
T 18	0.38	0.66	0.47	0.30	0.48	0.45	0.29	0.42	0.08	0.12	0.54	0.69	0.20	0.23	0.38	0.54	0.55	0.55	0.22	0.47	0.56	0.69	0.53	0.28	0.77
T 19	0.34	0.53	0.37	0.33	0.28	0.26	0.35	0.50	0.77	0.86	0.22	0.21	0.15	0.33	0.12	1.00	0.27	0.26	0.77	0.25	0.13	0.28	0.29	0.08	0.25
T 20	0.38	0.66	0.47	0.30	0.48	0.45	0.28	0.42	0.07	0.11	0.54	0.70	0.20	0.23	0.38	0.53	0.55	0.55	0.21	0.47	0.56	0.68	0.53	0.28	0.77
T 21	0.38	0.66	0.47	0.30	0.48	0.45	0.28	0.42	0.07	0.11	0.54	0.70	0.20	0.23	0.38	0.53	0.55	0.55	0.21	0.47	0.56	0.68	0.53	0.28	0.77
T 22	0.38	0.66	0.47	0.30	0.48	0.45	0.29	0.42	0.08	0.12	0.54	0.69	0.20	0.23	0.38	0.54	0.55	0.55	0.22	0.47	0.56	0.69	0.53	0.28	0.77
T 23	0.48	0.70	0.50	0.35	0.46	0.42	0.38	0.40	0.33	0.46	0.48	0.63	0.26	0.26	0.34	0.61	0.50	0.50	0.47	0.46	0.51	0.62	0.56	0.25	0.76
T 24	0.08	0.13	0.09	0.10	0.10	0.10	0.06	0.14	0.02	0.01	0.09	0.13	0.29	0.17	0.26	1.00	0.11	0.11	0.04	0.09	0.14	0.11	0.13	0.57	0.13
T 25	0.39	0.67	0.47	0.31	0.48	0.45	0.29	0.42	0.10	0.14	0.54	0.69	0.20	0.24	0.37	0.54	0.55	0.55	0.24	0.47	0.56	0.68	0.53	0.27	0.77

[illegible]

Table 6. Target’s adjusted other-evaluation results of bidders (herd coefficient $k = 0.3$).

	B 1	B 2	B 3	B 4	B 5	B 6	B 7	B 8	B 9	B 10	B 11	B 12	B 13	B 14	B 15	B 16	B 17	B 18	B 19	B 20	B 21	B 22	B 23	B 24	B 25	B 26
T 1	0.54	0.74	0.44	0.93	0.72	0.67	0.78	1.35	1.04	0.88	1.40	1.21	0.75	0.42	0.95	0.63	1.06	1.27	0.54	0.59	0.48	0.72	0.93	0.87	0.51	0.66
T 2	0.30	0.39	0.24	0.49	0.38	0.35	0.41	0.73	0.55	0.46	0.73	0.64	0.39	0.22	0.52	0.34	0.71	0.67	0.28	0.31	0.27	0.37	0.49	0.46	0.26	0.34
T 3	0.48	0.65	0.39	0.82	0.63	0.59	0.69	1.19	0.91	0.77	1.23	1.06	0.66	0.37	0.84	0.56	0.97	1.12	0.47	0.52	0.43	0.63	0.81	0.77	0.45	0.58
T 4	0.68	1.01	0.52	1.17	0.92	0.86	1.04	1.96	1.33	1.18	2.48	1.52	1.03	0.56	1.11	0.77	1.71	1.52	0.87	0.81	0.57	0.99	1.09	1.67	0.80	0.80
T 5	0.56	0.85	0.46	1.07	0.82	0.75	0.86	1.46	1.15	1.01	1.47	1.35	0.88	0.48	1.06	0.71	0.62	1.44	0.60	0.68	0.50	0.83	1.06	0.85	0.59	0.77
T 6	0.69	1.04	0.57	1.31	1.00	0.92	1.06	1.79	1.41	1.24	1.83	1.65	1.08	0.59	1.29	0.87	0.78	1.77	0.74	0.83	0.62	1.02	1.30	1.06	0.73	0.94
T 7	0.72	1.07	0.55	1.25	0.98	0.92	1.11	2.07	1.41	1.26	2.61	1.62	1.09	0.60	1.18	0.82	1.78	1.62	0.91	0.86	0.60	1.05	1.16	1.75	0.84	0.85
T 8	0.24	0.42	0.19	0.48	0.38	0.35	0.41	0.81	0.49	0.48	0.93	0.54	0.47	0.24	0.41	0.29	0.20	0.53	0.36	0.34	0.18	0.43	0.43	0.63	0.38	0.34
T 9	0.12	0.20	0.08	0.19	0.16	0.16	0.21	0.43	0.26	0.24	0.83	0.31	0.18	0.10	0.15	0.12	0.74	0.27	0.24	0.16	0.09	0.20	0.15	0.61	0.18	0.10
T 10	0.09	0.09	0.06	0.09	0.07	0.08	0.11	0.20	0.18	0.12	0.70	0.24	0.05	0.04	0.11	0.07	0.70	0.25	0.10	0.06	0.08	0.07	0.08	0.42	0.05	0.04
T 11	0.41	0.63	0.34	0.79	0.61	0.55	0.64	1.07	0.85	0.75	1.07	1.00	0.65	0.36	0.79	0.53	0.44	1.07	0.44	0.50	0.37	0.61	0.79	0.61	0.44	0.57
T 12	0.28	0.43	0.23	0.54	0.42	0.38	0.43	0.73	0.58	0.51	0.73	0.68	0.45	0.24	0.54	0.36	0.27	0.73	0.30	0.34	0.25	0.42	0.54	0.41	0.30	0.39
T 13	0.70	0.04	0.23	0.04	0.04	0.04	0.04	0.27	0.06	0.05	0.17	0.06	0.04	0.04	0.05	0.03	0.52	0.05	0.05	0.04	0.10	0.04	0.03	0.11	0.04	0.02
T 14	0.93	1.38	0.72	1.62	1.27	1.19	1.43	2.63	1.82	1.63	3.27	2.11	1.41	0.77	1.55	1.07	2.19	2.12	1.16	1.10	0.78	1.36	1.53	2.17	1.07	1.11
T 15	0.60	0.14	0.41	0.20	0.15	0.14	0.10	0.75	0.16	0.14	0.34	0.15	0.33	0.23	0.22	0.12	0.15	0.12	0.13	0.15	0.21	0.13	0.12	0.15	0.17	0.12
T 16	0.01	0.19	0.02	0.17	0.13	0.12	0.16	0.29	0.19	0.23	0.70	0.24	0.18	0.09	0.07	0.09	0.00	0.22	0.21	0.15	0.00	0.19	0.12	0.48	0.19	0.10
T 17	0.40	0.61	0.33	0.76	0.59	0.53	0.62	1.04	0.82	0.72	1.04	0.96	0.63	0.34	0.76	0.51	0.42	1.03	0.42	0.48	0.36	0.59	0.76	0.59	0.42	0.55
T 18	0.40	0.60	0.33	0.76	0.58	0.53	0.61	1.03	0.81	0.72	1.03	0.95	0.62	0.34	0.75	0.50	0.42	1.02	0.42	0.48	0.36	0.59	0.76	0.59	0.42	0.55
T 19	0.12	0.20	0.08	0.19	0.16	0.16	0.21	0.43	0.26	0.24	0.82	0.30	0.18	0.10	0.15	0.12	0.73	0.27	0.23	0.16	0.09	0.19	0.15	0.61	0.18	0.10
T 20	0.59	0.89	0.49	1.12	0.86	0.78	0.90	1.53	1.20	1.06	1.55	1.41	0.92	0.50	1.11	0.74	0.65	1.51	0.63	0.71	0.53	0.87	1.11	0.89	0.62	0.80
T 21	0.39	0.59	0.32	0.74	0.57	0.52	0.60	1.00	0.79	0.70	1.00	0.93	0.61	0.33	0.73	0.49	0.40	1.00	0.41	0.47	0.35	0.57	0.74	0.57	0.41	0.53
T 22	0.28	0.44	0.24	0.55	0.42	0.38	0.44	0.74	0.58	0.52	0.74	0.69	0.45	0.25	0.54	0.36	0.27	0.74	0.30	0.35	0.25	0.43	0.55	0.42	0.30	0.40
T 23	0.40	0.53	0.32	0.66	0.51	0.48	0.56	0.97	0.75	0.63	0.99	0.87	0.53	0.30	0.69	0.45	0.85	0.91	0.38	0.42	0.36	0.51	0.66	0.62	0.36	0.47
T 24	0.70	0.15	0.13	0.17	0.15	0.13	0.15	0.65	0.15	0.15	0.30	0.15	0.25	0.12	0.16	0.10	0.09	0.14	0.13	0.13	0.11	0.17	0.14	0.21	0.21	0.15
T 25	0.27	0.41	0.22	0.52	0.40	0.36	0.42	0.70	0.55	0.49	0.70	0.65	0.42	0.23	0.51	0.34	0.29	0.70	0.29	0.33	0.24	0.40	0.52	0.40	0.28	0.37

Table 7. Matching result (herd coefficient $k = 0.3$).

	B 1	B 2	B 3	B 4	B 5	B 6	B 7	B 8	B 9	B 10	B 11	B 12	B 13	B 14	B 15	B 16	B 17	B 18	B 19	B 20	B 21	B 22	B 23	B 24	B 25	B 26
T 1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 2	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 3	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 4	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 5	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
T 7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
T 8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
T 9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 11	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 12	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 14	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 15	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0

Table 7. *Cont.*[illegible]



Figure 2. Overall utility under different herd coefficients.

4.3. Discussion

The above experiment illustrates that our proposed method can provide decision makers an M&A matching strategy that makes the bidders and targets simultaneously satisfied with each other. In addition, here, we just experiment with the dataset of banks to illustrate our method; however, our method is applicable across any field. This is because our method is based on the DEA method, which is a driven comprehensive evaluation technique, and it does not require pre-setting production function parameters and yields objective evaluation results. Therefore, our model can operate and identify corresponding matching strategies once the values of the inputs and outputs of bidders and targets are known. In general, this new method possesses the following advantages.

First, our proposed method provides a new idea for two-side M&A matching from the efficiency evaluation. On the one hand, this method captures the competitiveness among homogeneous entities on the same side rather than relying solely on the information of individual bidders or targets. On the other hand, the efficiency evaluation based on DEA is a comprehensive evaluation that incorporates multiple inputs and outputs rather than focusing only on costs or profits. For example, in the banks' M&A matching, we seek the matching strategy based on their three inputs and three outputs. Together, these aspects enable us to identify two-side M&A matching strategies that better reflect real-world conditions. Second, we propose a new mutual evaluation method considering the herd behavior, and the matching model is based on such mutual evaluation results. By doing this, we improve the concept of cross efficiency and provide the mutual evaluation results in line with reality. Such mutual results can make the two-side M&A matching more acceptable than existing methods, because the above sensitivity analysis shows that the higher the herd coefficient, the greater the overall utility of bidders and targets. Third, our proposed method considers the bounded rationality of bidders and targets. The above experiment finds that different risk attitudes bring different matching results, which provide us good matching strategy based on decision makers' specific risk attitudes in practice. Finally, our proposed method simultaneously maximizes the bidders' and targets' satisfaction with each other. In general, our proposed method provides a new idea for the M&A matching, which can make the matching results consider more realistic factors than in previous studies.

5. Summary

An effective M&A hinges on a matching process that not only ensures high levels of satisfaction for both bidders and targets but also functions as a two-sided mechanism grounded in their mutual assessments. Previous studies mostly focus on the measurement of the potential gains of M&A, and a few studies on the M&A target or partner selection provide various solutions for M&A matching. However, these studies ignore the herd behavior of decision makers when the bidders and targets evaluate each other. In practice, one DMU's opinion is easy to be influenced by the opinions of those they trust. Furthermore, the M&A is a two-side matching, and the decision makers usually behave with bounded rationality. Based on these requirements and the literature gaps, we propose a new, two-side M&A matching strategy based on a perspective of the mutual evaluation considering the herd behavior. Finally, we apply our proposed method to the M&A matching among banks, including 25 targets and 26 bidders.

Our approach enhances the concept of cross efficiency in the DEA field and introduces a novel mutual evaluation method that accounts for herd behavior. Building upon this new mutual evaluation framework, we integrate DEA methodology, dual-sided theory, and prospect theory to explore two-side M&A matching strategies. This integration possesses three main advantages: (1) this method considers the herd behavior of decision makers during the mutual evaluation; (2) this method takes the bounded rationality of bidders and targets into account; and (3) this method simultaneously maximizes the bidders' and targets' satisfaction with each other. All these advantages make the matching strategy more accepted by M&A parties.

This study is limited by the small and selective dataset and the restrictive one-to-one matching assumption. Furthermore, our research is tested only on historical data without verification against actual M&A outcomes, thus limiting its practical applicability. Accordingly, there are several valuable research directions in the future. (1) We can apply our method into more real M&A scenarios and extend our method to multiple-to-multiple situations. (2) It is interesting to test whether our matching approach can contribute to the success of M&A activities. (3) We can validate the model's predictions by testing whether its identified "optimal" matches correspond to historically successful mergers and by analyzing the outcomes of unmatched DMUs. (4) It is also valuable to take into account the ambiguous information, moral hazard, and other uncertainties that may arise in M&A activities when matching the bidders and targets.

Author Contributions: Conceptualization, Y.W. and H.S.; methodology, Y.W. and H.S.; software, Y.W.; validation, Y.W. and H.S.; formal analysis, Y.W. and H.S.; investigation, Y.W. and H.S.; resources, Y.W. and H.S.; data curation, Y.W. and H.S.; writing—original draft preparation, Y.W.; writing—review and editing, Y.W. and H.S.; visualization, Y.W. and H.S.; supervision, H.S.; funding acquisition, Y.W. and H.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Natural Science Foundation of China, grant number 72401067, and the Social Science Foundation of Fujian Province, grant number FJ2023C025.

Data Availability Statement: The original contributions presented in this study are included in the present article. Further inquiries can be directed to the corresponding author.

Acknowledgments: We greatly appreciate the efforts of the reviewers and editorial team for our article.

Conflicts of Interest: The author declares no conflicts of interest.

Appendix A. Adjusted Other-Evaluation Results Under Different Herd Coefficients

Table A1. Target’s adjusted other-evaluation results of bidders (herd coefficient $k = 0.7$).

	B 1	B 2	B 3	B 4	B 5	B 6	B 7	B 8	B 9	B 10	B 11	B 12	B 13	B 14	B 15	B 16	B 17	B 18	B 19	B 20	B 21	B 22	B 23	B 24	B 25	B 26
T 1	0.70	1.03	0.57	1.28	0.98	0.91	1.06	1.82	1.41	1.22	1.93	1.65	1.05	0.58	1.28	0.86	1.14	1.74	0.75	0.82	0.63	1.00	1.27	1.17	0.72	0.91
T 2	0.15	0.19	0.12	0.25	0.19	0.18	0.21	0.36	0.28	0.23	0.36	0.32	0.20	0.11	0.26	0.17	0.33	0.34	0.14	0.15	0.13	0.19	0.25	0.23	0.13	0.17
T 3	0.56	0.81	0.45	1.01	0.78	0.72	0.84	1.45	1.12	0.97	1.53	1.31	0.83	0.46	1.01	0.68	0.94	1.38	0.60	0.65	0.50	0.79	1.00	0.94	0.57	0.72
T 4	1.08	1.75	0.85	2.02	1.58	1.47	1.79	3.24	2.30	2.08	4.45	2.70	1.75	0.95	1.87	1.32	2.65	2.73	1.50	1.39	0.92	1.71	1.88	2.93	1.36	1.35
T 5	0.79	1.20	0.66	1.50	1.15	1.05	1.22	2.06	1.62	1.43	2.11	1.90	1.23	0.68	1.49	1.00	0.97	2.03	0.85	0.95	0.71	1.16	1.49	1.23	0.83	1.08
T 6	1.09	1.65	0.90	2.07	1.59	1.45	1.68	2.85	2.23	1.97	2.93	2.62	1.70	0.93	2.05	1.37	1.35	2.80	1.18	1.31	0.98	1.61	2.05	1.72	1.15	1.48
T 7	1.17	1.89	0.92	2.19	1.71	1.59	1.93	3.49	2.49	2.25	4.75	2.92	1.89	1.03	2.03	1.43	2.83	2.96	1.61	1.50	1.00	1.85	2.04	3.12	1.47	1.47
T 8	0.13	0.31	0.10	0.33	0.26	0.24	0.29	0.55	0.35	0.36	0.83	0.40	0.33	0.16	0.25	0.19	0.13	0.39	0.29	0.25	0.10	0.31	0.28	0.56	0.28	0.22
T 9	0.06	0.14	0.04	0.13	0.11	0.11	0.14	0.28	0.18	0.17	0.59	0.21	0.13	0.07	0.09	0.08	0.38	0.20	0.16	0.11	0.05	0.14	0.10	0.42	0.13	0.07
T 10	0.04	0.04	0.03	0.04	0.03	0.03	0.05	0.08	0.08	0.05	0.30	0.10	0.02	0.02	0.05	0.03	0.30	0.11	0.04	0.03	0.03	0.03	0.04	0.18	0.02	0.02
T 11	0.46	0.68	0.38	0.86	0.66	0.60	0.69	1.17	0.92	0.81	1.17	1.08	0.70	0.39	0.86	0.57	0.54	1.16	0.48	0.54	0.41	0.66	0.86	0.68	0.47	0.62
T 12	0.14	0.22	0.12	0.28	0.21	0.19	0.22	0.37	0.30	0.26	0.37	0.35	0.23	0.12	0.27	0.18	0.14	0.37	0.15	0.17	0.13	0.21	0.28	0.21	0.15	0.20
T 13	0.30	0.08	0.10	0.08	0.06	0.06	0.08	0.22	0.09	0.10	0.32	0.11	0.08	0.05	0.05	0.04	0.22	0.10	0.10	0.07	0.04	0.08	0.06	0.22	0.08	0.04
T 14	1.66	2.61	1.31	3.07	2.39	2.22	2.68	4.81	3.47	3.11	6.30	4.06	2.63	1.44	2.89	2.01	3.77	4.14	2.18	2.08	1.42	2.56	2.89	4.10	2.00	2.08
T 15	0.26	0.13	0.18	0.15	0.11	0.10	0.10	0.43	0.14	0.14	0.39	0.15	0.21	0.13	0.12	0.08	0.06	0.13	0.13	0.12	0.09	0.12	0.09	0.24	0.14	0.09
T 16	0.00	0.08	0.01	0.07	0.06	0.05	0.07	0.13	0.08	0.10	0.30	0.10	0.08	0.04	0.03	0.04	0.00	0.10	0.09	0.06	0.00	0.08	0.05	0.21	0.08	0.04
T 17	0.42	0.63	0.35	0.80	0.61	0.56	0.64	1.09	0.86	0.75	1.09	1.00	0.65	0.36	0.79	0.53	0.50	1.08	0.44	0.50	0.38	0.61	0.79	0.63	0.44	0.57
T 18	0.41	0.62	0.34	0.78	0.60	0.55	0.63	1.07	0.84	0.74	1.07	0.99	0.64	0.35	0.78	0.52	0.49	1.06	0.43	0.49	0.37	0.60	0.78	0.62	0.43	0.56
T 19	0.06	0.14	0.04	0.13	0.11	0.10	0.14	0.27	0.17	0.17	0.58	0.21	0.12	0.07	0.09	0.08	0.37	0.19	0.16	0.11	0.05	0.14	0.10	0.41	0.13	0.07
T 20	0.86	1.29	0.71	1.62	1.24	1.14	1.32	2.23	1.75	1.54	2.28	2.05	1.33	0.73	1.61	1.08	1.04	2.19	0.92	1.03	0.77	1.26	1.61	1.33	0.90	1.16
T 21	0.39	0.58	0.32	0.73	0.56	0.51	0.59	1.00	0.79	0.69	1.00	0.93	0.60	0.33	0.73	0.49	0.46	0.99	0.41	0.46	0.35	0.57	0.73	0.58	0.40	0.53
T 22	0.15	0.23	0.13	0.29	0.22	0.20	0.23	0.39	0.31	0.28	0.39	0.37	0.24	0.13	0.29	0.19	0.15	0.39	0.16	0.18	0.14	0.23	0.29	0.22	0.16	0.21
T 23	0.37	0.52	0.30	0.65	0.50	0.47	0.54	0.94	0.72	0.62	0.97	0.84	0.53	0.30	0.66	0.44	0.65	0.89	0.38	0.42	0.33	0.51	0.65	0.60	0.36	0.46
T 24	0.31	0.18	0.07	0.18	0.14	0.13	0.16	0.46	0.18	0.20	0.56	0.21	0.22	0.10	0.11	0.10	0.04	0.20	0.19	0.15	0.05	0.19	0.14	0.39	0.20	0.12
T 25	0.12	0.18	0.10	0.22	0.17	0.15	0.18	0.30	0.24	0.21	0.30	0.28	0.18	0.10	0.22	0.15	0.13	0.30	0.12	0.14	0.10	0.17	0.22	0.17	0.12	0.16

Table A2. Target’s adjusted other-evaluation results of bidders (herd coefficient $k = 0.5$).

	B 1	B 2	B 3	B 4	B 5	B 6	B 7	B 8	B 9	B 10	B 11	B 12	B 13	B 14	B 15	B 16	B 17	B 18	B 19	B 20	B 21	B 22	B 23	B 24	B 25	B 26
T 1	0.62	0.88	0.50	1.11	0.85	0.79	0.92	1.59	1.22	1.05	1.66	1.43	0.90	0.50	1.12	0.74	1.10	1.51	0.65	0.70	0.55	0.86	1.10	1.02	0.62	0.78
T 2	0.23	0.29	0.18	0.37	0.28	0.27	0.31	0.54	0.42	0.34	0.54	0.48	0.29	0.17	0.39	0.25	0.52	0.50	0.21	0.23	0.20	0.28	0.37	0.34	0.20	0.26
T 3	0.52	0.73	0.42	0.92	0.71	0.65	0.76	1.32	1.02	0.87	1.38	1.19	0.74	0.41	0.93	0.62	0.95	1.25	0.53	0.58	0.46	0.71	0.91	0.85	0.51	0.65
T 4	0.88	1.38	0.69	1.60	1.25	1.17	1.42	2.60	1.81	1.63	3.47	2.11	1.39	0.76	1.49	1.04	2.18	2.12	1.18	1.10	0.74	1.35	1.49	2.30	1.08	1.07
T 5	0.68	1.02	0.56	1.29	0.98	0.90	1.04	1.76	1.38	1.22	1.79	1.62	1.06	0.58	1.27	0.85	0.79	1.74	0.72	0.81	0.61	1.00	1.28	1.04	0.71	0.92
T 6	0.89	1.35	0.74	1.69	1.29	1.18	1.37	2.32	1.82	1.61	2.38	2.14	1.39	0.76	1.67	1.12	1.07	2.28	0.96	1.07	0.80	1.31	1.68	1.39	0.94	1.21
T 7	0.95	1.48	0.74	1.72	1.34	1.25	1.52	2.78	1.95	1.75	3.68	2.27	1.49	0.81	1.61	1.12	2.31	2.29	1.26	1.18	0.80	1.45	1.60	2.44	1.16	1.16
T 8	0.18	0.36	0.14	0.40	0.32	0.29	0.35	0.68	0.42	0.42	0.88	0.47	0.40	0.20	0.33	0.24	0.16	0.46	0.33	0.30	0.14	0.37	0.35	0.59	0.33	0.28
T 9	0.09	0.17	0.06	0.16	0.13	0.13	0.18	0.35	0.22	0.21	0.71	0.26	0.15	0.08	0.12	0.10	0.56	0.23	0.20	0.14	0.07	0.17	0.13	0.52	0.15	0.08
T 10	0.06	0.06	0.04	0.06	0.05	0.06	0.08	0.14	0.13	0.09	0.50	0.17	0.04	0.03	0.08	0.05	0.50	0.18	0.07	0.05	0.06	0.05	0.06	0.30	0.04	0.03
T 11	0.44	0.65	0.36	0.83	0.63	0.58	0.67	1.12	0.89	0.78	1.12	1.04	0.68	0.37	0.82	0.55	0.49	1.12	0.46	0.52	0.39	0.64	0.82	0.64	0.45	0.59
T 12	0.21	0.32	0.18	0.41	0.31	0.29	0.33	0.55	0.44	0.39	0.55	0.51	0.34	0.18	0.40	0.27	0.20	0.55	0.23	0.26	0.19	0.32	0.41	0.31	0.23	0.30
T 13	0.50	0.06	0.17	0.06	0.05	0.05	0.06	0.25	0.07	0.07	0.25	0.08	0.06	0.04	0.05	0.04	0.37	0.07	0.07	0.05	0.07	0.06	0.04	0.17	0.06	0.03
T 14	1.29	2.00	1.02	2.35	1.83	1.71	2.05	3.72	2.65	2.37	4.79	3.08	2.02	1.11	2.22	1.54	2.98	3.13	1.67	1.59	1.10	1.96	2.21	3.14	1.54	1.60
T 15	0.43	0.13	0.29	0.18	0.13	0.12	0.10	0.59	0.15	0.14	0.37	0.15	0.27	0.18	0.17	0.10	0.11	0.13	0.13	0.14	0.15	0.13	0.10	0.19	0.15	0.10

Table A2. Cont.

	B 1	B 2	B 3	B 4	B 5	B 6	B 7	B 8	B 9	B 10	B 11	B 12	B 13	B 14	B 15	B 16	B 17	B 18	B 19	B 20	B 21	B 22	B 23	B 24	B 25	B 26
T 16	0.01	0.13	0.01	0.12	0.10	0.09	0.12	0.21	0.14	0.16	0.50	0.17	0.13	0.06	0.05	0.06	0.00	0.16	0.15	0.11	0.00	0.14	0.09	0.34	0.13	0.07
T 17	0.41	0.62	0.34	0.78	0.60	0.55	0.63	1.06	0.84	0.74	1.06	0.98	0.64	0.35	0.78	0.52	0.46	1.05	0.43	0.49	0.37	0.60	0.78	0.61	0.43	0.56
T 18	0.41	0.61	0.34	0.77	0.59	0.54	0.62	1.05	0.83	0.73	1.05	0.97	0.63	0.35	0.76	0.51	0.45	1.04	0.43	0.49	0.36	0.59	0.77	0.60	0.42	0.55
T 19	0.09	0.17	0.06	0.16	0.13	0.13	0.18	0.35	0.22	0.21	0.70	0.26	0.15	0.08	0.12	0.10	0.55	0.23	0.20	0.13	0.07	0.17	0.13	0.51	0.15	0.08
T 20	0.72	1.09	0.60	1.37	1.05	0.96	1.11	1.88	1.47	1.30	1.91	1.73	1.13	0.62	1.36	0.91	0.85	1.85	0.77	0.87	0.65	1.06	1.36	1.11	0.76	0.98
T 21	0.39	0.58	0.32	0.74	0.56	0.51	0.59	1.00	0.79	0.70	1.00	0.93	0.60	0.33	0.73	0.49	0.43	0.99	0.41	0.46	0.35	0.57	0.73	0.57	0.40	0.53
T 22	0.22	0.33	0.18	0.42	0.32	0.29	0.34	0.57	0.45	0.40	0.57	0.53	0.35	0.19	0.41	0.28	0.21	0.57	0.23	0.27	0.19	0.33	0.42	0.32	0.23	0.30
T 23	0.38	0.52	0.31	0.66	0.51	0.47	0.55	0.95	0.73	0.62	0.98	0.86	0.53	0.30	0.68	0.45	0.75	0.90	0.38	0.42	0.34	0.51	0.66	0.61	0.36	0.47
T 24	0.51	0.16	0.10	0.17	0.15	0.13	0.15	0.56	0.17	0.18	0.43	0.18	0.23	0.11	0.14	0.10	0.06	0.17	0.16	0.14	0.08	0.18	0.14	0.30	0.21	0.14
T 25	0.19	0.29	0.16	0.37	0.28	0.26	0.30	0.50	0.40	0.35	0.50	0.46	0.30	0.17	0.37	0.24	0.21	0.50	0.20	0.23	0.17	0.28	0.37	0.29	0.20	0.27

Table A3. Target's adjusted other-evaluation results of bidders (herd coefficient $k = 0$).

	B 1	B 2	B 3	B 4	B 5	B 6	B 7	B 8	B 9	B 10	B 11	B 12	B 13	B 14	B 15	B 16	B 17	B 18	B 19	B 20	B 21	B 22	B 23	B 24	B 25	B 26
T 1	0.42	0.53	0.33	0.67	0.52	0.49	0.57	1.00	0.76	0.63	1.00	0.88	0.53	0.30	0.71	0.46	1.00	0.92	0.38	0.42	0.38	0.51	0.67	0.64	0.36	0.47
T 2	0.42	0.53	0.33	0.67	0.52	0.49	0.57	1.00	0.76	0.63	1.00	0.88	0.53	0.30	0.71	0.46	1.00	0.92	0.38	0.42	0.38	0.51	0.67	0.64	0.36	0.47
T 3	0.42	0.53	0.33	0.67	0.52	0.49	0.57	1.00	0.76	0.63	1.00	0.88	0.53	0.30	0.71	0.46	1.00	0.92	0.38	0.42	0.38	0.51	0.67	0.64	0.36	0.47
T 4	0.38	0.46	0.28	0.54	0.43	0.41	0.49	1.00	0.59	0.51	1.00	0.64	0.49	0.27	0.54	0.36	1.00	0.61	0.39	0.37	0.30	0.46	0.50	0.72	0.38	0.38
T 5	0.38	0.59	0.32	0.74	0.57	0.52	0.59	1.00	0.79	0.70	1.00	0.93	0.61	0.33	0.73	0.49	0.36	1.00	0.41	0.47	0.34	0.57	0.74	0.56	0.41	0.54
T 6	0.38	0.59	0.32	0.74	0.57	0.52	0.60	1.00	0.79	0.70	1.00	0.93	0.61	0.33	0.73	0.49	0.36	1.00	0.41	0.47	0.34	0.57	0.74	0.57	0.41	0.54
T 7	0.38	0.46	0.28	0.54	0.43	0.41	0.49	1.00	0.59	0.51	1.00	0.64	0.49	0.27	0.54	0.36	1.00	0.61	0.39	0.37	0.30	0.46	0.50	0.72	0.38	0.38
T 8	0.32	0.51	0.25	0.59	0.47	0.43	0.50	1.00	0.59	0.57	1.00	0.65	0.58	0.30	0.53	0.37	0.25	0.64	0.42	0.41	0.25	0.52	0.54	0.67	0.45	0.44
T 9	0.16	0.25	0.11	0.24	0.19	0.20	0.27	0.55	0.33	0.30	1.00	0.37	0.21	0.12	0.20	0.15	1.00	0.33	0.29	0.20	0.12	0.24	0.19	0.75	0.22	0.12
T 10	0.12	0.12	0.09	0.13	0.10	0.11	0.16	0.28	0.26	0.17	1.00	0.35	0.07	0.06	0.16	0.11	1.00	0.36	0.15	0.09	0.11	0.10	0.12	0.60	0.07	0.05
T 11	0.38	0.59	0.32	0.74	0.57	0.52	0.59	1.00	0.79	0.70	1.00	0.93	0.61	0.33	0.73	0.49	0.36	1.00	0.41	0.47	0.34	0.57	0.74	0.56	0.41	0.54
T 12	0.38	0.59	0.32	0.74	0.57	0.52	0.59	1.00	0.79	0.70	1.00	0.93	0.61	0.33	0.73	0.49	0.36	1.00	0.41	0.47	0.34	0.57	0.74	0.56	0.41	0.54
T 13	1.00	0.01	0.32	0.02	0.02	0.02	0.01	0.31	0.03	0.01	0.06	0.02	0.01	0.04	0.06	0.02	0.75	0.01	0.02	0.01	0.15	0.01	0.01	0.04	0.01	0.00
T 14	0.38	0.46	0.28	0.54	0.43	0.41	0.49	1.00	0.59	0.51	1.00	0.64	0.49	0.27	0.54	0.36	1.00	0.61	0.39	0.37	0.30	0.46	0.50	0.72	0.38	0.38
T 15	0.86	0.15	0.58	0.24	0.19	0.17	0.10	1.00	0.18	0.14	0.30	0.15	0.43	0.31	0.29	0.15	0.22	0.11	0.13	0.18	0.31	0.13	0.13	0.08	0.19	0.15
T 16	0.02	0.27	0.02	0.25	0.19	0.17	0.23	0.42	0.27	0.33	1.00	0.34	0.26	0.12	0.10	0.12	0.00	0.32	0.31	0.22	0.00	0.27	0.17	0.69	0.27	0.14
T 17	0.38	0.59	0.32	0.74	0.57	0.52	0.60	1.00	0.79	0.70	1.00	0.93	0.61	0.33	0.73	0.49	0.36	1.00	0.41	0.47	0.34	0.57	0.74	0.57	0.41	0.54
T 18	0.38	0.59	0.32	0.74	0.57	0.52	0.60	1.00	0.79	0.70	1.00	0.93	0.61	0.33	0.73	0.49	0.36	1.00	0.41	0.47	0.34	0.57	0.74	0.57	0.41	0.54
T 19	0.16	0.25	0.11	0.24	0.19	0.20	0.27	0.55	0.33	0.30	1.00	0.37	0.21	0.12	0.20	0.15	1.00	0.33	0.29	0.20	0.12	0.24	0.19	0.75	0.22	0.12
T 20	0.38	0.59	0.32	0.74	0.57	0.52	0.59	1.00	0.79	0.70	1.00	0.93	0.61	0.33	0.73	0.49	0.36	1.00	0.41	0.47	0.34	0.57	0.74	0.56	0.41	0.54
T 21	0.38	0.59	0.32	0.74	0.57	0.52	0.60	1.00	0.79	0.70	0.99	0.93	0.61	0.33	0.73	0.49	0.36	1.00	0.41	0.47	0.34	0.57	0.74	0.56	0.41	0.54
T 22	0.38	0.59	0.32	0.74	0.57	0.52	0.60	1.00	0.79	0.70	1.00	0.93	0.61	0.33	0.73	0.49	0.36	1.00	0.41	0.47	0.34	0.57	0.74	0.57	0.41	0.54
T 23	0.42	0.53	0.33	0.67	0.52	0.49	0.57	1.00	0.76	0.63	1.00	0.88	0.53	0.30	0.71	0.46	1.00	0.92	0.38	0.42	0.38	0.51	0.67	0.64	0.36	0.47
T 24	1.00	0.12	0.18	0.16	0.15	0.13	0.13	0.80	0.12	0.11	0.10	0.11	0.27	0.13	0.20	0.10	0.13	0.10	0.09	0.11	0.16	0.15	0.15	0.08	0.21	0.17
T 25	0.39	0.58	0.32	0.74	0.56	0.52	0.60	1.00	0.79	0.70	1.00	0.93	0.60	0.33	0.73	0.49	0.42	1.00	0.41	0.46	0.35	0.57	0.74	0.57	0.40	0.53

Appendix B. Matching Results Under Different Herd Coefficients

Table A4. Matching result (herd coefficient $k = 0.7$).

	B 1	B 2	B 3	B 4	B 5	B 6	B 7	B 8	B 9	B 10	B 11	B 12	B 13	B 14	B 15	B 16	B 17	B 18	B 19	B 20	B 21	B 22	B 23	B 24	B 25	B 26
T 1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 2	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 3	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
T 5	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
T 7	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
T 9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 11	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 12	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 14	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
T 17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
T 18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
T 19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
T 21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
T 22	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 23	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
T 24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 25	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table A5. Matching result (herd coefficient $k = 0.5$).

[illegible]

Table A5. *Cont.*[illegible]

Table A6. Matching result (herd coefficient $k = 0$).

	B 1	B 2	B 3	B 4	B 5	B 6	B 7	B 8	B 9	B 10	B 11	B 12	B 13	B 14	B 15	B 16	B 17	B 18	B 19	B 20	B 21	B 22	B 23	B 24	B 25	B 26
T 1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 2	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 3	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
T 5	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 6	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
T 8	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 11	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 12	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
T 15	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 16	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 17	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
T 18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
T 19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
T 20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
T 21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
T 22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
T 23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
T 24	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 25	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Appendix C. Matching Results Under Different Risk Attitudes

Table A7. Matching result (herd coefficient $k = 0.3$, risk parameter $\alpha = 0.5$, $\beta = 0.3$ and $\mu = 3$).

	B 1	B 2	B 3	B 4	B 5	B 6	B 7	B 8	B 9	B 10	B 11	B 12	B 13	B 14	B 15	B 16	B 17	B 18	B 19	B 20	B 21	B 22	B 23	B 24	B 25	B 26
T 1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
T 3	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
T 5	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
T 7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
T 8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
T 9	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 11	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
T 13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
T 15	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
T 17	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 18	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
T 21	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
T 22	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
T 24	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T 25	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

References

- Chang, T.S.; Lin, J.G.; Ouenniche, J. DEA-based Nash bargaining approach to merger target selection. *Eur. J. Oper. Res.* **2023**, *305*, 930–945. [\[CrossRef\]](#)
- Zhu, Q.; Li, X.; Li, F.; Amirteimoori, A. Data-driven approach to find the best partner for merger and acquisitions in banking industry. *Ind. Manag. Data Syst.* **2021**, *121*, 879–893. [\[CrossRef\]](#)
- Li, F.; Liang, L.; Li, Y.; Emrouznejad, A. An alternative approach to decompose the potential gains from mergers. *J. Oper. Res. Soc.* **2018**, *69*, 1793–1802. [\[CrossRef\]](#)
- Wanke, P.; Maredza, A.; Gupta, R. Merger and acquisitions in South African banking: A network DEA model. *Res. Int. Bus. Financ.* **2017**, *41*, 362–376. [\[CrossRef\]](#)
- Zhu, Q.; Wu, J.; Chu, J.; Amirteimoori, A.; Sun, J. DEA-based models for best partner selection for merger. *Rairo-Oper. Res.* **2017**, *51*, 1345–1357. [\[CrossRef\]](#)
- Huang, Q.; Jiang, F.; Xie, F. The dark side of industry tournament incentives. *Eur. Corp. Gov. Inst.-Financ. Work. Pap.* **2020**, 684. [\[CrossRef\]](#)
- Koi-Akrofi, G.Y. Mergers and acquisitions failure rates and perspectives on why they fail. *Int. J. Innov. Appl. Stud.* **2016**, *17*, 150–158.
- Charnes, A.; Cooper, W.W.; Rhodes, E. Measuring the efficiency of decision making units. *Eur. J. Oper. Res.* **1978**, *2*, 429–444. [\[CrossRef\]](#)
- Vaidya, O.S.; Kumar, S. Analytic hierarchy process: An overview of applications. *Eur. J. Oper. Res.* **2006**, *169*, 1–29. [\[CrossRef\]](#)
- Kumbhakar, S.C.; Lovell, C.K. *Stochastic Frontier Analysis*; Cambridge University Press: Cambridge, UK, 2003.
- Sexton, T.R.; Silkman, R.H.; Hogan, A.J. Data envelopment analysis: Critique and extensions. *New Dir. Program Eval.* **1986**, *32*, 73–105. [\[CrossRef\]](#)
- Zhang, R.; Wei, Q.; Li, A.; Ren, L. Measuring efficiency and technology inequality of China's electricity generation and transmission system: A new approach of network Data Envelopment Analysis prospect cross-efficiency models. *Energy* **2022**, *246*, 123274. [\[CrossRef\]](#)
- Jin, F.; Cai, Y.; Zhou, L.; Ding, T. Regret-rejoice two-stage multiplicative DEA models-driven cross-efficiency evaluation with probabilistic linguistic information. *Omega-Int. J. Manag. Sci.* **2023**, *117*, 102839. [\[CrossRef\]](#)
- Yang, M.; Wang, Z.; Liang, L. A novel centralized cross-efficiency evaluation via explainable artificial intelligence in the context of big data. *Eur. J. Oper. Res.* **2025**, *327*, 247–262. [\[CrossRef\]](#)
- Wu, N.; Zhang, M.; Huang, Y.; Wang, J. Staged Resource Allocation Optimization under Heterogeneous Grouping Based on Interval Data: The Case of China's Forest Carbon Sequestration. *Mathematics* **2024**, *12*, 2650. [\[CrossRef\]](#)
- Banerjee, A.V. A simple model of herd behavior. *Q. J. Econ.* **1992**, *107*, 797–817. [\[CrossRef\]](#)
- Rook, L. An economic psychological approach to herd behavior. *J. Econ. Issues* **2006**, *40*, 75–95. [\[CrossRef\]](#)
- Ajraldi, V.; Pittavino, M.; Venturino, E. Modeling herd behavior in population systems. *Nonlinear. Anal.-Real.* **2011**, *12*, 2319–2338. [\[CrossRef\]](#)
- Ma, J.; Wang, D.; McBean, E.A.; Su, J. A group decision-making method for public opinion response plans: Herd behavior and two-stage consensus-reaching. *Expert Syst. Appl.* **2025**, *268*, 126367. [\[CrossRef\]](#)
- Wu, D.D.; Zhou, Z.; Birge, J.R. Estimation of potential gains from mergers in multiple periods: A comparison of stochastic frontier analysis and Data Envelopment Analysis. *Ann. Oper. Res.* **2011**, *186*, 357–381. [\[CrossRef\]](#)
- Wu, D.D.; Luo, C.; Wang, H.; Birge, J.R. Bi-level programming merger evaluation and application to banking operations. *Prod. Oper. Manag.* **2016**, *25*, 498–515. [\[CrossRef\]](#)
- Al Tamimi, H.A.H.; Duqi, A.; Kanas, A.; Zervopoulos, P.D. Directional distance function DEA estimators for evaluating efficiency gains from possible mergers and acquisitions. *J. Oper. Res. Soc.* **2022**, *73*, 1240–1257. [\[CrossRef\]](#)
- Lin, Y.; Wang, Y.M.; Shi, H.L. Mergers and acquisitions matching for performance improvement: A DEA-based approach. *Econ. Res.-Ekon. Istraz.* **2020**, *33*, 3545–3561. [\[CrossRef\]](#)
- Shi, H.L.; Wang, Y.M. A merger and acquisition matching method that considers irrational behavior from a performance perspective. *IEEE Access* **2020**, *8*, 45726–45737. [\[CrossRef\]](#)
- Saen, R.F.; Karimi, B.; Fathi, A. Unleashing efficiency potential: The power of non-convex double frontiers in sustainable transportation supply chains. *Socio-Econ. Plan. Sci.* **2025**, *98*, 102143. [\[CrossRef\]](#)
- Kaffash, S.; Azizi, R.; Huang, Y.; Zhu, J. A survey of data envelopment analysis applications in the insurance industry 1993–2018. *Eur. J. Oper. Res.* **2020**, *284*, 801–813. [\[CrossRef\]](#)
- Mirmozaffari, M.; Shadkam, E.; Khalili, S.M.; Kabirifar, K.; Yazdani, R.; Asgari Gashteroodkhani, T. A novel artificial intelligent approach: Comparison of machine learning tools and algorithms based on optimization DEA Malmquist productivity index for eco-efficiency evaluation. *Int. J. Energy Sect. Manag.* **2021**, *15*, 523–550. [\[CrossRef\]](#)
- Kao, C.; Liu, S.T. A compromise solution approach for efficiency measurement with shared input: The case of tourist hotels in Taiwan. *Eur. J. Oper. Res.* **2025**, *321*, 895–906. [\[CrossRef\]](#)

29. Banker, R.D.; Charnes, A.; Cooper, W.W. Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Manag. Sci.* **1984**, *30*, 1078–1092.
30. Tone, K. A slacks-based measure of efficiency in data envelopment analysis. *Eur. J. Oper. Res.* **2001**, *130*, 498–509. [[CrossRef](#)]
31. Toloo, M.; Tone, K.; Izadikhah, M. Selecting slacks-based data envelopment analysis models. *Eur. J. Oper. Res.* **2023**, *308*, 1302–1318. [[CrossRef](#)]
32. Guevel, H.P.; Ramón, N.; Aparicio, J. Benchmarking and Target Setting in Weight Restriction Context. *Mathematics* **2025**, *13*, 1175. [[CrossRef](#)]
33. Ghiyasi, M.; Nasrabadi, N.; Emrouznejad, A. Inverse DEA based on cost and revenue efficiency in the absence of price information. *Expert Syst. Appl.* **2025**, *284*, 128028. [[CrossRef](#)]
34. Lozano, S.; Villa, G. DEA-based pre-merger planning tool. *J. Oper. Res. Soc.* **2010**, *61*, 1485–1497. [[CrossRef](#)]
35. Shi, X.; Li, Y.; Emrouznejad, A.; Xie, J.; Liang, L. Estimation of potential gains from bank mergers: A novel two-stage cost efficiency DEA model. *J. Oper. Res. Soc.* **2017**, *68*, 1045–1055. [[CrossRef](#)]
36. Hsu, S.Y.; Lu, C.C.; Xiao, Y.H.; Chiu, Y.H. Two-stage evaluation of the pre-merger potential gains of Taiwan financial holding companies: Dynamic network slack-based measure analysis approach. *Comput. Econ.* **2024**, *64*, 2131–2178. [[CrossRef](#)]
37. Santín, D.; Tejada, J. Is it worth it? Using DEA to analyze the efficiency gains and costs of merging university departments: A case study of the Complutense University of Madrid. *Int. Trans. Oper. Res.* **2025**, *32*, 2593–2619. [[CrossRef](#)]
38. Soltanifar, M.; Ghiyasi, M.; Emrouznejad, A.; Sharafi, H. A novel model for merger analysis and target setting: A CSW-Inverse DEA approach. *Expert Syst. Appl.* **2024**, *249*, 123326. [[CrossRef](#)]
39. Gerami, J. Strategic alliances and partnerships based on the semi-additive production technology in DEA. *Expert Syst. Appl.* **2024**, *251*, 123986. [[CrossRef](#)]
40. Lozano, S. Using DEA to find the best partner for a horizontal cooperation. *Comput. Ind. Eng.* **2013**, *66*, 286–292. [[CrossRef](#)]
41. Boamah, M.I.; Amin, G.R. Partner selection in business mergers: A data envelopment analysis approach. *Rairo-Oper. Res.* **2024**, *58*, 3107–3117. [[CrossRef](#)]
42. Alam, N.; Lee Ng, S. Banking mergers—an application of matching strategy. *Rev. Account. Financ.* **2014**, *13*, 2–23. [[CrossRef](#)]
43. Ullah, N.; Rashid, M.M. Merger and acquisition strategy for banks—an extensive contemporary literature review. *Educ. Res. (IJMCER)* **2024**, *6*, 41–55.
44. Kahneman, D.; Tversky, A. Prospect theory: An analysis of decisions under risk. *Econometrica* **1979**, *47*, 263–291. [[CrossRef](#)]
45. Tversky, A.; Kahneman, D. Advances in prospect theory: Cumulative representation of uncertainty. *J. Risk Uncertain.* **1992**, *5*, 297–323. [[CrossRef](#)]
46. Goursat, L. Essays on Matching with Limited Information and Bounded Rationality. Ph.D. Thesis, PSE—École d’Économie de Paris, Paris, France, 2024.
47. Liu, H.H.; Song, Y.Y.; Yang, G.L. Cross-efficiency evaluation in data envelopment analysis based on prospect theory. *Eur. J. Oper. Res.* **2019**, *273*, 364–375. [[CrossRef](#)]
48. Bikhchandani, S.; Hirshleifer, D.; Welch, I. Learning from the behavior of others: Conformity, fads, and informational cascades. *J. Econ. Perspect.* **1998**, *12*, 151–170. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.