Economic Research-Ekonomska Istraživanja

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/rero20

Mergers and acquisitions matching for performance improvement: a DEA-based approach

Yang Lin, Ying-Ming Wang & Hai-Liu Shi

To cite this article: Yang Lin, Ying-Ming Wang & Hai-Liu Shi (2020) Mergers and acquisitions matching for performance improvement: a DEA-based approach, Economic Research-Ekonomska Istraživanja, 33:1, 3545-3561, DOI: 10.1080/1331677X.2020.1775673

To link to this article: https://doi.org/10.1080/1331677X.2020.1775673

Published online: 18 Sep 2020.

ECONOMIC RESEARCH-EKONOMSKA ISTRAŽIVANJA
2020, VOL. 33, NO. 1, 3545–3561
https://doi.org/10.1080/1331677X.2020.1775673

Routledge
Taylor & Francis Group

OPEN ACCESS Check for updates

Mergers and acquisitions matching for performance improvement: a DEA-based approach

Yang Lin[a], Ying-Ming Wang[b] and Hai-Liu Shi[c]

[a]School of Economics, Fujian Normal University, Fuzhou, China; [b]Decision Sciences Institute, Fuzhou University, Fuzhou, China; [c]School of Electronic Information Science, Fujianjiangxia University, Fuzhou, China

ABSTRACT
This article proposes a new data envelopment analysis (DEA)-based approach to deal with mergers and acquisitions (M&As) matching. To derive reliable matching degrees between bidder and target firms, we consider both technical efficiency and scale efficiency. Specifically, an inverse DEA model is developed for measuring the technical efficiency, while a conventional DEA model is employed to identify the return of scale of the merged decision-making units (DMUs). Then, an optimization model is formulated to generate matching results to improve DMUs' performance. An empirical study of M&As matching Turkish energy firms is examined to illustrate the proposed approach. This study shows that both technical efficiency and scale efficiency have impacts on M&As matching practices.

ARTICLE HISTORY
Received 25 January 2020
Accepted 21 May 2020

KEYWORDS
Mergers and acquisitions; two-sided matching; inverse DEA; technical efficiency; returns to scale

JEL CLASSIFICATIONS
C3; C44; C78

1. Introduction

Mergers and acquisitions (M&As) refer to amalgamation or consolidation of firms through various types of business and financial transactions (Braguinsky et al., 2015; Vizcaíno-González & Navío-Marco, 2018). Often such consolidation is represented as a bidder (acquirer) firm takes over another target firm, and establishes itself as a new entity. As one of the most ordinary affairs in the corporate world, M&As are recognized as one of the most essential ways of entering a new market, accelerating globalization, reducing business risk and improving competitive edge (Steigenberger, 2017).

Typically M&As are associated with the characteristic of two-sided matching (TSM) (Gale & Shapley, 1962; Roth, 1982), where each participant aims to form a profitable coalition with a partner under acceptable matching criteria. In the framework of TSM, the matching degrees among the candidates (acquirer or target) on two sides need to be derived before applying a specific strategy. For achieving this a variety of evaluating methods have been utilized. Data envelopment analysis, which based on linear programming, is one of the most important techniques among them

CONTACT Yang Lin linyang42@163.com

and has been proved an effective way for performance assessment (Charnes et al., 1978, Liang et al. 2008, Cook & Seiford, 2009, Zheng et al., 2018).

Participants during an M&A naturally care about if the merged firm can operate in a global efficient way. The implication of the global efficiency is twofold within the framework of DEA. On one hand, can it produce the maximum outputs by consuming the minimum required resources, which refers to the problem of technical efficiency in economic field (Farrell, 1957; Yannick et al., 2016). On the other hand, does the combined size of the new firm is too large to manufacture agilely, which refers to the problem of scale efficiency (Banker & Thrall, 1992). Usually, a bidder is reluctant to accept a merger without an improvement in scale efficiency. Sometimes, participants are expected to learn the maximum possible profit after an M&A. In other words, they may probably be more interested in how much they can earn in the future instead of the immediate profit of the present moment. So a challenge is how to calculate the maximum outputs as well as technical efficiency of a merged DMU under the given inputs. However, as an ex-post planning tool, DEA is typically used for efficiency evaluation under the existing information and cannot provide mechanisms for ex-ante prediction (Amin & Oukil, 2019). An alternative approach for dealing with this problem is the inverse DEA (InvDEA), which developed by Wei et al. (2000) based on the theory of inverse linear programming. In contrast to conventional DEA models, the InvDEA assumes the relative efficiency as a parameter and determines the best possible outputs (or inputs) that are required to achieve the efficiency goal.

This study aims to address the strategic matching in M&A considering both technical efficiency and scale efficiency, where the technical efficiency is measured using an optimal efficiency of each DMU and scale efficiency captures the impact of scale size on productivity (Banker et al. 1984). The main contribution and novelty lies in that we develop a new approach by integrating the InvDEA with return to scale (RTS) measurement to obtain the matching degree, and present a streamlined approach for M&A decision. Specifically, an InvDEA model is formulated to estimate the technical efficiency of the merged DMUs, and a traditional DEA model is employed to identify their scale efficiency. Furthermore, both the two efficiencies are aggregated to generate the matching degrees. As can be seen later, the proposed approach can deal with M&A matching without explicit preference provided by the two-sided participants.

The remainder of this article is organized as follows: Section 2 reviews related theories. Section 3 briefly introduces the CCR and basic InvDEA model; In Section 4, the proposed approach for M&A matching is developed; Section 5 gives an empirical study of M&A matching about Turkish energy-related firms; finally, conclusions are drawn in Section 6.

2. Literature review

Mergers and acquisitions (M&As) have been an important way for modern firms to reposition organizations in a constantly changing market. A successful M&A could result in technological advances and value creation (Chanmugam et al., 2005; Halkos & Tzeremes, 2013), yet huge losses such that costs rising, profits declining, or resources waste would occur due to an unfit M&A (Qian et al., 2017). By scanning the literature, there have been plenty of studies about the various process in M&A over the past few decades, such as acquisition planning, potential target searching, purchase contract, or financing negotiations, etc. (DeYoung et al., 2009). This article focuses on one critical step in M&A, the M&A matching (or fit), which refers to the procedure of mutual election between bidders and targets.

One important theoretical foundation of M&A matching is the methodology of two-sided matching (TSM). TSM initially originated from the problem of marriage and college admission (Gale & Shapley, 1962). Many economic systems can be modeled as TSM markets, with a sort of preference for each candidate on one side over the potential partners on another side. TSM now has been broadly applied across a wide spectrum of socio-economic activities, such as electronic brokering (Jiang et al., 2011; Le et al., 2018), person-job fit (Azevedo, 2014; Lin et al., 2019a), venture capital matching (Sørensen, 2007), mergers and acquisitions (Akkus et al., 2016; Park, 2013; Shi et al., 2017; Wanke et al., 2019), etc. An introductory survey of TSM has been carried out by Roth and Sotomayor (1992); Bando et al. (2016) also summarized some existing matching models with externalities.

As to the issue of M&A matching, primary research streams can be categorized into three domains: strategic matching, organizational matching and resource-based matching (Tsai, 2000). The first one focuses on strategic relevance of bidders and targets, and the integration of information and resources driven by profit sharing and mutual incentive. Salter and Weinhold (1979) firstly introduced the notion of strategic matching into M&A, and distinguished them as the relevant and irrelevant acquisition; Chen et al. (2018) focused on the strategic matching of M&As in Chinese banking industry by employing a new stochastic frontier method. Cartwright and Schoenberg (2006) discussed some possible reasons causing failure of acquisitions, especially when a target firm has close commercial links with the acquirer. The second organizational matching is paid attention to matching effect on soft power such that cultural and institutional incentives of a merged company; Cartwright and Cooper (1993) argued that a successful organizational matching would benefit the partnership from a positive synergy effect on organizational culture and personnel exchange. The third strand of research examines the overall coordination of both sides from the angle of each own resource and the transferability of resource caused by the potential synergy effects. Wernerfelt (1995) introduced the concept of resource position barrier and suggested that analyzing the acquisition behavior of firms from the resource perspective; based on the viewpoint of resource sharing, Capron and Pistre (2002) addressed the mechanisms of value creation and transfer within M&A.

Prior to an M&A transaction, how to measure the matching degree of a bidder and a target from either side should be addressed. It is relatively simple if the candidates have preferences over the partners, and the goal is to pair them to achieve a maximum matching degree under the given criteria. Nevertheless, it is not easy for participants to consider all aspects in detail and give preference over the candidates directly due to the complexity of M&A practices. As a non-parametric mathematical tool for assessing the relative efficiency of a set of DMUs, DEA is powerful in handling such evaluation problems (Wang & Chin, 2010). Following the original CCR model (Charnes et al. 1978), many classical models have been proposed in DEA literature, such as the BCC model, the slacks-based measure, and the cross-efficiency evaluation. Under the context of M&A, one line of study aims at investigating the efficiency of the gains after an M&A. Bogetoft and Wang (2005) established an economic production model to calculate the potential gains from mergers by the CCR model; Kristensen et al. (2010) followed Bogetoft and Wang's work and advised a DEA-based model to examine the hospital mergers in Denmark. Taking Singapore banks as the background, Sufian and Majid (2007) applied DEA to examine the efficiency gains (or loss) resulting in a merger. Rahman et al. (2016) conducted an empirical study about the banking company mergers in US through the method of DEA window analysis. Shi et al. (2017) employed the cross-efficiency DEA to derive a matching degree in M&A with participants' contrasting attitudes. By assuming a DMU is composed of two or more candidates, Shi et al. (2018) developed a novel two-stage DEA model to decompose and calculate the potential gains from an M&A.

DEA is often applied as a post-merger analysis tool that focusing on the assessment of gain and loss under the observed information. On the contrary, some scholars attempted to use InvDEA instead of DEA to address pre-merger analysis. This reversed technique is a helpful managerial tool in dealing with problems such as resource allocation (Hadi-Vencheh et al., 2008), investment optimization (Chen et al., 2017), and production prediction (Lin et al., 2019b). Especially, the InvDEA facilitates pre-analysis as it deems the given efficiency as a parameter and optimizes the outputs (or inputs). By scanning the literature, there are merely a few studies on M&A using the InvDEA method. Gattoufi et al. (2014) developed an InvDEA method for strategic merger decisions in the banking industry. Amin and Oukil (2019) addressed a new InvDEA model with a flexible target setting, and applied this model in university merger practices. Amin et al. (2019) also combined the goal programming method with InvDEA in target setting of an M&A in the banking industry. Based on the above literature review, the research of M&A practices based on InvDEA has attracted scholars' attention gradually, but more efforts still need to be done.

3. Theoretical background

3.1. CCR model

Consider there exist n DMUs, each $DMU_j(j=1,\ 2,\dots,n)$ has m inputs $x_{ij}(i=1,\ 2,\dots,m)$ and s outputs $y_{rj}(r=1,2,\dots,s)$. For theDMU_0 under evaluation, its relative efficiency can be measured by the CCR model (Charnes et al., 1978):

$$\begin{gathered}\max \sum_{r=1}^{s} u_r y_{r0} \\ \text{s.t.} \sum_{i=1}^{m} v_i x_{i0} = 1 \\ \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0, j = 1, 2, \dots, n \\ u_r, v_i \ge 0, r = 1, 2, \dots, s, i = 1, 2, \dots, m\end{gathered} \tag{1}$$

where v_i is the weight of the ith input and u_r is the weight of the rth output.

The dual model of CCR model (1) is formulated as,

$$
\begin{aligned}
&\min\ \theta_0\\
&\text{s.t.}\sum_{j=1}^{n}\lambda_j x_{ij} \le \theta_0 x_{i0}, i = 1, 2, \ldots, m\\
&\sum_{j=1}^{n}\lambda_j y_{rj} \ge y_{r0}, r = 1, 2, \ldots, s\\
&\lambda_j \ge 0, \quad j = 1, 2, \ldots, n
\end{aligned} \tag{2}
$$

where θ_0 is a real variable of DMU_0 and $\lambda_j (j = 1,\ 2, \ldots, n)$ is an intensity vector. DMU_0 is referred to as CCR-efficient if $\theta_0 = 1$. Model (2) is estimated under a constant RTS assumption as the sum of λ_j is unconstrained. The constraint $\sum_j \lambda_j > 1$, $\sum_j \lambda_j < 1$, or $\sum_j \lambda_j = 1$ can be imposed on model (2), which implies a decreasing, increasing, or variable RTS, respectively (Banker & Thrall, 1992).

3.2. Basic InvDEA model

In the context of inverse DEA, as its name indicate, the situation is reversed where input or output levels are to be assessed with a given efficiency score (Ghiyasi, 2015; Jahanshahloo et al., 2015). If the outputs of DMU_0 are increased from y_0 to $\beta_0 = y_0 + \Delta y_0$, and the inputs are changed from x_0 to $\alpha_0 = x_0 + \Delta x_0$, then the following model is constructed to estimate the minimum input increment $\Delta \boldsymbol{x}_0$(Ghiyasi, 2015),

$$
\begin{aligned}
&\min\ \Delta \boldsymbol{x}_0 = (\Delta x_{10}, \Delta x_{20}, \ldots, \Delta x_{m0})\\
&\text{s.t.}\sum_{j=1}^{n}\lambda_j x_{ij} + \lambda_{0'}(x_{i0} + \Delta x_{i0}) \le \theta_0^*(x_{i0} + \Delta x_{i0}), i = 1, 2, \ldots, m\\
&\sum_{i=1}^{n}\lambda_j y_{ij} + \lambda_{0'}(y_{r0} + \Delta y_{r0}) \ge y_{r0} + \Delta y_{r0}, r = 1, 2, \ldots, s\\
&x_{i0} + \Delta x_{i0} \ge 0, i = 1, 2, \ldots, m\\
&\lambda_j, \lambda_{0'} \ge 0, j = 1, 2, \ldots, n
\end{aligned} \tag{3}
$$

where θ_0^* is a given relative efficiency of DMU_0. Note that model (3) is based on the multi-objective linear programming, which solved by integrating the multiple objectives into a single one.

4. Methodological framework

Assume there are n firms in matching market and viewed as n DMUs (DMU_j, $j = 1, 2, \ldots, n$). During M&As matching, these firms will be classified into two subgroups, the bidder firms $B = \{DMU_b : b = 1, 2, \ldots, g\}$ and the target firms $T = \{DMU_t : t = 1, 2, \ldots, h\}$ $(B \cap T = \emptyset)$. A bidder firm (DMU) is accompanied by a CCR-efficiency $\theta_b = 1$, otherwise, it belongs to the other side. We limit our study to one-to-one M&A matching and introduce some hypotheses below:

Hypothesis 1 Each bidder firm takes over at most one target firm, and vice versa.

Hypothesis 2(a) Firms involved in M&A are concerned about the potential benefit.
Hypothesis 2(b) Firms involved in M&A are concerned about the economies of scale.

4.1. Derivation of technical efficiency using InvDEA

To begin with, we take the DMU_b and DMU_t for illustration. Suppose an M&A is achieved between them and denoted this newly merged DMU as $DMU_{b\&t}$, $(b \in B, t \in T)$. Inspired by model (3), the following output-oriented InvDEA model is considered to estimate the maximum outputs of $DMU_{b\&t}$:

$$\begin{aligned} &\max \sum_{r=1}^{s} w_r \beta_{r,b\&t} \\ \text{s.t.} &\sum_{j \in \{N-b-t\}} \lambda_j x_{ij} + (x_{ib} + x_{it})\lambda_{b\&t} \le x_{ib} + x_{it}, i = 1, 2, \ldots, m \\ &\sum_{j \in \{N-b-t\}} \lambda_j y_{rj} + (y_{rb} + y_{rt})\lambda_{b\&t} \ge \theta^*_{b\&t}\beta_{r,b\&t}, r = 1, 2, \ldots, s \\ &\sum_{j \in \{N-b-t\}} \lambda_j + \lambda_{b\&t} = 1 \\ &\lambda_j \ge 0, \lambda_{b\&t} \ge 0, j \in \{N-b-t\} \end{aligned} \tag{4}$$

In model (4), the vector $\boldsymbol{\beta}_{b\&t} = (\beta_{1,b\&t}, \beta_{2,b\&t}, \ldots, \beta_{s,b\&t})$ is the maximum possible outputs of $DMU_{b\&t}$, and the $\theta^*_{b\&t}$ is a given efficiency score. Let us discuss some further explanations about this model: 1) the new $DMU_{b\&t}$ is usually expected to be efficient, and its efficiency score is presumed to be 1.0; 2) The input amount $x_{ib} + x_{it}$ of $DMU_{b\&t}$ is obtained by simple summation of them; 3) The $w_r(r = 1, 2, \ldots, s)$ is a given weighting parameter, and equal weights are assigned for them.

Theorem 1. *For each merged $DMU_{b\&t}$, it exists $\max \sum_{r=1}^{s} w_r \beta_{r,b\&t} \ge \sum_{r=1}^{s} w_r(y_{rb} + y_{rt})$.*

Proof. It is easy to verify $\beta_{r,b\&t} = y_{rb} + y_{rt}$ when $\lambda_{b\&t} = 1$, $\lambda_j = 0(r = 1, 2, \ldots, s)$, and the equation $\sum_{r=1}^{s} w_r \beta_{r,b\&t} = \sum_{r=1}^{s} w_r(y_{rb} + y_{rt})$ is hold for any $w_r \in [0, 1]$. So there is at least one feasible solution to model (4) for a given DMU. On the other hand, the maximum value of $\sum_{r=1}^{s} w_r \beta_{r,b\&t}$ is not less than any convex combination of y_{rb} and y_{rt}, namely, $\max \sum_{r=1}^{s} w_r \beta_{r,b\&t} \ge \sum_{r=1}^{s} w_r(y_{rb} + y_{rt})$.

Theorem 1 indicates the combination of output amounts may be increased or unchanged after an M&A. However, a single output such that $\beta_{r,b\&t}$ is allowed to be less than its parented output $y_{rb} + y_{rt}$ $(r = 1, 2, \ldots, s)$. Clearly, a higher value of this function value signifies a better matching result. Following this idea, we derive the technical efficiency $\pi_{b\&t}$ of the $DMU_{b\&t}$ and express as below,

$$\pi_{b\&t} = \frac{\sum_{r=1}^{s} (\beta_{r,b\&t} - y_{rb} - y_{rt})}{\max_{t \in \{1,2,\ldots,h\}} \sum_{r=1}^{s} (\beta_{r,b\&t} - y_{rb} - y_{rt})}, \quad b \in B, t \in T \tag{5}$$

4.2. Measurement of RTS

Scale efficiency tells whether a firm operates at an optimal scale. There are three types of RTS: increasing, constant, and decreasing. We calculate the RTS of the merged $DMU_{b\&t}$ to estimate its productivity in an M&A. Inspired by the dual model (2), the model for evaluating the scale efficiency of $DMU_{b\&t}$ is expressed as,

$$\begin{aligned} &\max\ \theta_{b\&t} \\ \text{s.t.} &\sum_{j\in\{N-b-t\}} \lambda_j x_{ij} + (x_{ib}+x_{it})\lambda_{b\&t} \le \theta_{b\&t}(x_{ib}+x_{it}), i=1,2,\ldots,m \\ &\sum_{j\in\{N-b-t\}} \lambda_j y_{rj} + (y_{rb}+y_{rt})\lambda_{b\&t} \ge y_{rb}+y_{rt}, r=1,2,\ldots,s \\ &\lambda_j \ge 0, \lambda_{b\&t} \ge 0 \end{aligned} \tag{6}$$

Model (6) may produce multiple optimal solutions, which would affect the feasibility of scale efficiency evaluation. To resolve this problem, a secondary goal method is employed to maximize the sum of the non-negative vector $\boldsymbol{\lambda}$:

$$\begin{aligned} &\max \sum_{j\in\{N-b-t\}} \lambda'_j + \lambda'_{b\&t} \\ \text{s.t.} &\sum_{j\in\{N-b-t\}} \lambda'_j x_{ij} + (x_{ib}+x_{it})\lambda'_{b\&t} \le \theta^*_{b\&t}(x_{ib}+x_{it}), i=1,2,\ldots,m \\ &\sum_{j\in\{N-b-t\}} \lambda'_j y_{rj} + (y_{rb}+y_{rt})\lambda'_{b\&t} \ge y_{rb}+y_{rt}, r=1,2,\ldots,s \\ &\sum_{j\in\{N-b-t\}} \lambda_j + \lambda_{b\&t} \le 1 \\ &\lambda'_j \ge 0, \lambda'_{b\&t} \ge 0 \end{aligned} \tag{7}$$

where $\lambda'_j, j \in \{N-b-t\}$ and $\lambda'_{b\&t}$ are the optimal solutions solved by model (6).

Let $\omega_{b\&t} = \sum_{j\in\{N-b-t\}} \lambda'_j + \lambda'_{b\&t}$, if $\omega_{b\&t} \le 1$, then no further treatment is needed for the scale efficiency. The remaining case, i.e.,$\omega_{b\&t}>1$ is addressed by replacing the constraint$\sum_{j\in\{N-b-t\}} \lambda_j + \lambda_{b\&t}>1$ in this model. According to Banker and Thrall (1992), the RTS situation of $DMU_{b\&t}$ can be identified as,

1. $\omega_{b\&t}<1$, then the RTS of $DMU_{b\&t}$ is increasing, which implies the scale efficiency of the merged firm would be promoted after an M&A. This situation is desirable and will be accepted by both bidder and target.
2. $\omega_{b\&t} = 1$, then the RTS of $DMU_{b\&t}$ is constant, which implies the scale efficiency of the merged firm would be unchanged after an M&A. This situation is also acceptable.
3. $\omega_{b\&t}>1$, then the RTS of $DMU_{b\&t}$ is decreasing, which implies the scale efficiency of the merged firm is going to downsize. This situation is undesirable and generally will be rejected by a DMU on either side.

Taking into account the above identification rule, we derive the following expression for calculating the scale efficiency,

$$f(\omega_{b\&t}) = \begin{cases} 1/\omega_{b\&t}, & \omega_{b\&t} \leq 1 \\ -\omega_{b\&t}, & \omega_{b\&t} > 1 \end{cases} \tag{8}$$

It is worth pointing out that a decreasing RTS is assigned with a negative value and will be eliminated by our presented approach.

4.3. Two-sided M&A matching

After conducting the previous two stages, the technical efficiency and scale efficiency for a potential one-to-one match can be calculated. Both of them determine the final matching degree together.

Let $\Pi = [\pi_{b\&t}]_{g\times h}$ and $\Omega = [f(\omega_{b\&t})]_{g\times h}$ be the matrices of technical efficiency and scale efficiency related to DMUs on either side. By introducing the 0–1 variables$x_{b\&t}(b = 1,2,\ldots,g,\ \ t = 1,2,\ldots,h)$, where$x_{b\&t} = 1$ means DMU_b and DMU_t are merged and$x_{b\&t} = 0$, otherwise. Thus, the following optimization model can be established:

$$\begin{aligned} \max \sum_{t\in T}\sum_{b\in B} \pi_{b\&t} f(\omega_{b\&t}) x_{b\&t} \\ \text{s.t.} \sum_{b\in B} x_{b\&t} \leq 1, t \in T \\ \sum_{t\in T} x_{b\&t} \leq 1, b \in B \\ x_{b\&t} = 0 or 1 \end{aligned} \tag{9}$$

where the $\pi_{b\&t} f(\omega_{b\&t})$ is the matching degree between the DMUs of DMU_b and DMU_t. The mechanism of model (9) is to find out the maximum sum of matching degree among the DMUs on two sides. Note that any bidder (or target) would match no more than one target (or bidder) as the constraints imposed on the solution. Since model (9) is a linear program, it can be solved directly.

5. Case study

5.1. M&A in Turkish energy firms

Within the past decades, Turkey has witnessed great economic development and become one of the largest economies in the Middle East region. Nevertheless, rapid industrial growth was accompanied by overuse as well as misuse of energy resources. As a non-oil producing country, a practical resource regulation is vital for sustainable energy consumption in Turkey. On the other hand, one characteristic of Turkish energy firms is they generally are small or medium-sized institutions that have more difficulties in production due to the economic scale effects. Therefore, appropriate mergers and acquisitions are widespread in the Turkish energy industry.

Nowadays, a great number of small or medium businesses are located along Turkey's Marmara Sea. As energy production involves a huge amount of resource consumption, the industrial energy uses are treated as the multiple inputs of a firm (DMU). In this study, we apply the developed method to the M&A matching decision

Table 1. Variables of the DMUs.

Variables	Unit/per year	Notation
Electricity consumption	Kilowatt Hour	x_1
Natural gas consumption	Cubic Meter	x_2
Oil consumption	Tons	x_3
Liquefied petroleum gas	Tons	x_4
Sales revenue	Dollar	y_1
Total profit	Dollar	y_2

Source: The authors.

Table 2. Original data and CCR-efficiencies of the 20 DMUs.

	Variable						
DMUs	x_1	x_2	x_3	x_4	y_1	y_2	CCR
DMU_1	900,500	950,600	750	240	3,376,100	1,350,000	0.912
DMU_2	1,150,000	875,500	1100	380	7,342,200	2,345,150	1.00
DMU_3	870,900	750,000	1320	600	5,750,000	945,000	1.00
DMU_4	1,350,300	800,300	600	350	5,666,600	1,340,145	1.00
DMU_5	1,450,400	1,100,200	1270	540	3,998,200	1,142,350	0.439
DMU_6	1,250,700	695,600	980	270	4,775,600	1,191,600	0.850
DMU_7	1,450,600	925,500	845	570	8,540,460	2,875,600	1.00
DMU_8	1,050,300	874,100	890	382	6,553,000	1,650,300	1.00
DMU_9	1,025,800	750,400	1100	210	5,518,680	640,000	1.00
DMU_{10}	1,362,000	1,013,000	1140	652	6,171,450	850,000	0.728
DMU_{11}	1,164,500	986,300	685	715	5,915,410	1,243,000	0.862
DMU_{12}	985,600	752,410	950	458	3,345,600	1,450,650	0.722
DMU_{13}	875,650	795,620	850	710	4,645,340	932,500	0.831
DMU_{14}	1,256,100	1,025,130	741	465	6,163,420	1,320,400	0.862
DMU_{15}	1,187,940	1,000,200	985	698	5,514,300	2,300,450	0.959
DMU_{16}	963,540	874,150	750	450	2,945,300	420,000	0.497
DMU_{17}	898,800	754,360	810	640	3,781,300	145,000	0.667
DMU_{18}	1,201,000	854,010	1040	654	4,658,400	1,410,000	0.628
DMU_{19}	1,132,300	950,200	1002	485	4,785,420	987,500	0.672
DMU_{20}	978,500	875,600	1100	695	3,574,120	254,000	0.566

Source: The authors.

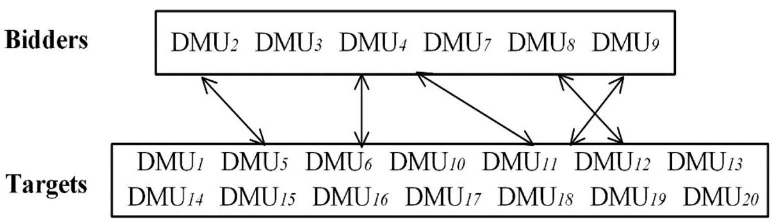

Figure 1. Description of the 20 DMUs on two sides. *Source*: The authors.

for 20 energy-related firms that were selected from the Istanbul region. Each one of these firms (DMUs) has four inputs $x_i(i = 1, 2, 3, 4)$ and two outputs $y_i(i = 1, 2)$. The detailed description of these factors is presented in Table 1. The original data of the 20 DMUs are derived from the published work (Önüt & Soner, 2007) and listed in Table 2, where the last column is the CCR-efficiency of each DMU.

According to the obtained CCR-efficiencies, the 20 DMUs are divided into the bidder subgroup and the target subgroup on two sides, as illustrated in Figure 1.

Based on model (4) the InvDEA model is iteratively constructed to estimate the maximum potential outputs between the one-to-one M&A matching pairs. Since there are 6 bidders and 14 target firms, the InvDEA model should be solved 6×14

Table. 3 Technical efficiencies of the merged DMUs.

	Bidder					
$\pi_{b\&t}$	DMU_2	DMU_3	DMU_4	DMU_7	DMU_8	DMU_9
DMU_1	0.0	0.0	0.0	0.345	0.082	0.0
DMU_5	0.0	0.445	0.0	0.0	0.087	0.088
DMU_6	0.742	0.0	0.0	0.646	0.485	0.918
DMU_{10}	0.878	0.225	0.0	0.611	0.0	0.939
DMU_{11}	0.0	0.0	0.812	0.0	0.0	0.653
DMU_{12}	0.413	0.0	0.034	0.0	0.047	0.0
DMU_{13}	0.0	0.0	0.632	0.0	1.0	0.0
DMU_{14}	0.0	0.0	1.0	0.0	0.0	0.147
DMU_{15}	0.069	0.0	0.731	0.428	0.536	0.446
DMU_{16}	0.0	0.118	0.046	1.0	0.0	0.097
DMU_{17}	1.0	0.340	0.040	0.0	0.640	0.0
DMU_{18}	0.692	0.138	0.0	0.539	0.0	1.0
DMU_{19}	0.0	0.0	0.0	0.220	0.0	0.0
DMU_{20}	0.0	1.0	0.0	0.0	0.0	0.70

Source: The authors.

Table 4. Matching degrees of the merged DMUs.

	Bidder					
$\pi_{b\&t}f(\omega_{b\&t})$	DMU_2	DMU_3	DMU_4	DMU_7	DMU_8	DMU_9
DMU_1	0.0	0.0	0.0	0.506	−0.103	0.0
DMU_5	0.0	0.470	0.0	0.0	0.110	0.088
DMU_6	0.742	0.0	0.0	0.755	0.589	1.082
DMU_{10}	1.017	0.225	0.0	−0.975	0.0	0.939
DMU_{11}	0.0	0.0	1.063	0.0	0.0	0.796
DMU_{12}	−0.610	0.0	0.041	0.0	0.047	0.0
DMU_{13}	0.0	0.0	0.690	0.0	−1.669	0.0
DMU_{14}	0.0	0.0	1.0	0.0	0.0	0.170
DMU_{15}	0.070	0.0	−0.904	0.576	0.639	0.523
DMU_{16}	0.0	0.159	0.054	1.083	0.0	−0.120
DMU_{17}	1.142	−0.503	0.040	0.0	0.839	0.0
DMU_{18}	−1.271	−0.226	0.0	0.539	0.0	1.582
DMU_{19}	0.0	0.0	0.0	0.220	0.0	0.0
DMU_{20}	0.0	1.340	0.0	0.0	0.0	−0.825

Source: The authors.

times and each time for a different matching pair. After that, the technical efficiency $\pi_{b\&t}(b \in B, t \in T)$ can be obtained via Eq. (5), which listed in Table 3.

Additionally, the scale efficiencies $\omega_{b\&t}(b \in B, t \in T)$ can be yielded by using models (6) and (7). The normalized scale efficiencies $f(\omega_{b\&t})$ can be further generated with Eq. (8). By multiplying the $\pi_{b\&t}$ with the$f(\omega_{b\&t})$ correspondingly, the matching degrees of all possible merged DMUs can be derived as (Table 4),

So the matching programming is established by model (9) as,

$$\begin{aligned}
\max\ & \pi_{2\&1}f(\omega_{2\&1})x_{2\&1} + \pi_{2\&5}f(\omega_{2\&5})x_{2\&5} + \ldots + \pi_{2\&20}f(\omega_{2\&20})x_{2\&20} + \ldots \\
& \ldots + \pi_{9\&1}f(\omega_{9\&1})x_{9\&1} + \pi_{9\&5}f(\omega_{9\&5})x_{9\&5} + \ldots\ldots + \pi_{9\&20}f(\omega_{9\&20})x_{9\&20} \\
\text{s.t.}\ & x_{2\&t} + x_{3\&t} + x_{4\&t} + x_{7\&t} + x_{8\&t} + x_{9\&t} \leq 1, \quad t = 1, 5, 6, 10, 11, \ldots, 20 \\
& x_{b\&1} + x_{b\&5} + x_{b\&6} + x_{b\&10} + x_{b\&11} + \ldots\ldots + x_{b\&20} \leq 1, b = 2, 3, 4, 7, 8, 9 \\
& x_{b\&t} = 0or1, \quad b = 2, 3, 4, 7, 8, 9; t = 1, 5, 6, 10, 11, \ldots, 20
\end{aligned}$$

Solving this model by Lingo 11.0, the optimal solution is respectively obtained as:$x_{2\&17} = x_{3\&20} = x_{4\&11} = x_{7\&16} = x_{8\&5} = x_{9\&18} = 1$. So the matching results are:

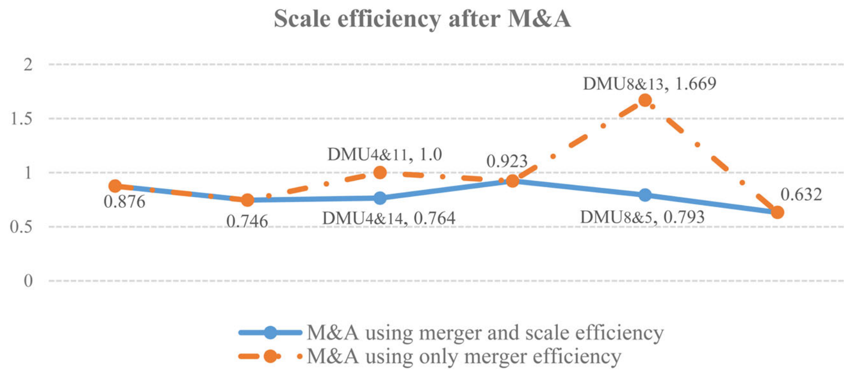

Figure 2. Comparison of the scale efficiencies. *Source*: The authors.

$$\left\{ \begin{array}{c} DMU_2 \leftrightarrow DMU_{17}, DMU_3 \leftrightarrow DMU_{20}, DMU_4 \leftrightarrow DMU_{11}, \\ DMU_7 \leftrightarrow DMU_{16}, DMU_8 \leftrightarrow DMU_5, DMU_9 \leftrightarrow DMU_{18} \end{array} \right\}.$$

5.2. Analysis and discussion

We firstly analyze the matching results only using the technical efficiencies of the DMUs. Substituting the data in Table 3 into model (10), the matching results are obtained as below:

$$\left\{ \begin{array}{c} DMU_2 \leftrightarrow DMU_{17}, DMU_3 \leftrightarrow DMU_{20}, DMU_4 \leftrightarrow DMU_{14}, \\ DMU_7 \leftrightarrow DMU_{16}, DMU_8 \leftrightarrow DMU_{13}, DMU_9 \leftrightarrow DMU_{18} \end{array} \right\}$$

Obviously, there are some differences comparing with the previous results, where the bidder DMU_4 is now matched with the target DMU_{14}, and the DMU_8 is matched with the DMU_{13}. The varying scale efficiencies of the merged DMUs are summarized in Figure 2. Compared with the previous results that all DMUs are identified as increasing RTS, we found this time the scale efficiencies of $DMU_{8\&13}$ and $DMU_{4\&11}$ are 1.669 and 1.0, which signifying decreasing RTS and constant RTS, respectively. That is because some pairs with higher scale efficiencies may have been matched up by model (9). Yet our method eliminates this possibility directly by imposing the constraint (8).

Now we compare the CCR-efficiencies of the obtained merged DMUs using the original input and output amounts. It is well known that CCR model can be used for evaluating the global efficiency (i.e., pure technical efficiency and scale efficiency) of a DMU. As shown in Figure 3, there are some varieties of the two DMUs, namely, the $DMU_{3\&20}$ and $DMU_{9\&18}$, where both of them have a lower efficiency if calculating only with the technical efficiency. This demonstrates they have not achieved optimal resource allocation especially when considering scale measurement. It is suggested to enhance the DMUs' performance by taking both technical and scale efficiencies into account in an M&A matching practice. In our approach, the matching degree $\pi_{b\&t} f(\omega_{b\&t})$ in model (9) can be regarded as an integrative factor for the two

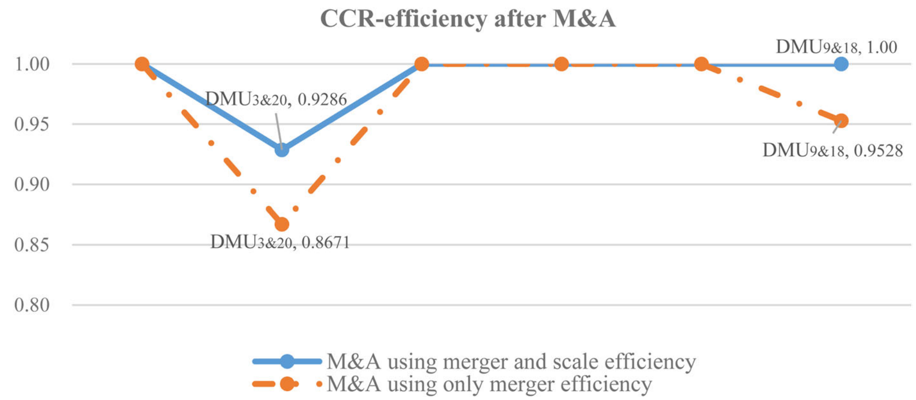

Figure 3. Calculating results of CCR-efficiency. *Source*: The authors.

Table 5. Output weights derived by different methods.

Approach	Reference	Output weights
Least-square method	Xu et al. (2013)	(0.4652, 0.5348)
CCSD method	Wang and Luo (2010)	(0.3822, 0.6178)
Chi-square method	Wang et al. (2007)	(0.4086, 0.5814)
The proposed method	This article	(0.50, 0.50)

Source: The authors.

efficiency measures, which remedy this deficiency to some extent. Besides, this result also supports the hypothesis 2 introduced in Section 4.

As is seen from model (4), the determination of output weights $w_r(r=1,\ 2)$ would have an effect on the objective function. Many weighting methods have been developed in the existing literature. Next we compare the weights of output variables with several popular methods, as shown in Table 5.

From Table 5, the results have slight differences among these methods. However, the weight values of w_2 obtained are all larger than those of w_1. The technical efficiency of each DMU can be calculated in a similar way. Except for the CCSD method, the other two methods achieve the same matching results as we do.

Finally, we conduct a comparison with the method in Shi et al. (2017). They developed an approach for M&A matching using cross-efficiency model with contrasting attitudes. To facilitate the comparison, we only set the efficiency floor parameter in their model as$\theta^L_{d\&k} = 0.7$. Afterwards, the feasible matching matrix is calculated based on the matrices of technical efficiency and scale efficiency. Then the optimal results are generated as:

$$\left\{ \begin{array}{c} DMU_2 \leftrightarrow DMU_{17}, DMU_3 \leftrightarrow DMU_{13}, DMU_4 \leftrightarrow DMU_6, \\ DMU_7 \leftrightarrow DMU_{16}, DMU_8 \leftrightarrow DMU_5, DMU_9 \leftrightarrow DMU_{18} \end{array} \right\}$$

The above results are somewhat different from those obtained by our approach. The bidder DMU_3 is suggested to acquire the targetDMU_{20}, and the bidder DMU_4 is recommend to acquire the target DMU_6 by Shi et al. (2017)'s method, which is different from the merged $DMU_{3\&13}$ and $\mathrm{DMU}_{4\&11}$ obtained by our method. Figure 4 depicts the CCR-efficiencies derived by the two methods. There are two DMUs of

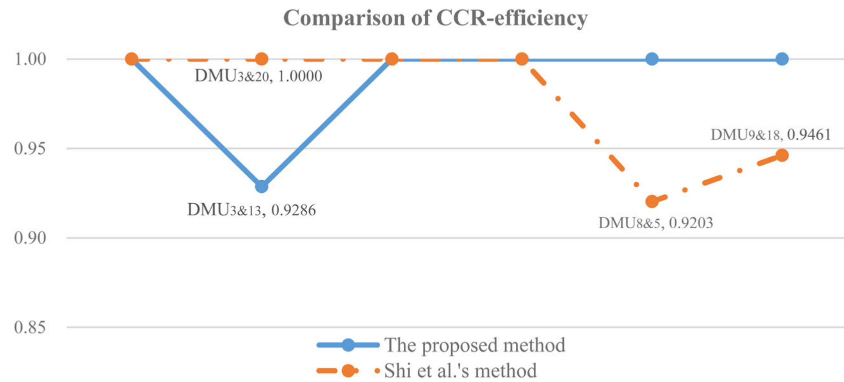

Figure 4. CCR-efficiencies obtained by two different methods. *Source*: The authors.

$DMU_{8\&5}$ and $DMU_{9\&18}$ are evaluated as inefficient through Shi et al.'s approach. In contrast, the merged $DMU_{3\&13}$ generated by our approach has a lower efficiency score of 0.9286. The distinction lies in that different methods are applied in calculating the technical efficiency since both of them have considered the score efficiency. As a matter of fact, there are many existing DEA models can be used to determine the relative efficiencies. But in the present study, we are more interested in predicting the maximum potential production of a merged DMU rather than measuring the production at the current level of inputs.

5.3. Managerial implications

Based on the insights discussed before, we summarize the following implications for M&A matching:

1. Two-sided matching is a promising and attractive way for M&As when there are available candidates for bidders or targets on either side. Compared with the developed two-sided M&A matching in this article, there is another kind of one-sided matching in the existing works (Okumura, 2017). These models regard the bidder as the dominant part and mainly focuses on the bidder's willingness (or preference), but neglect the target's willingness to sell or cooperate. During a practical M&A, a bidder or a target has the option to match or reject according to his own interests. Therefore, a satisfied matching result is more likely to be achieved when considering both sides' demand and requirement.
2. It is suggested to take both technical efficiency and scale efficiency into consideration during an M&A matching. Thanks to the resource dependence, high investment and high risk of energy-related firms, analysis of RTS of the merged firms is a critical step to ensure an acceptable result. When a merged DMU is evaluated only on the basis of the technical efficiency, as shown in Figure 2, it may be not a practical solution with a decreasing RTS.

6. Concluding remarks

This article presents an M&A matching framework for the strategic decision based on DEA techniques. The idea of our approach is to combine technical efficiency and scale efficiency for calculating the matching degree between participants. Corresponding, an InvDEA and a conventional DEA models are constructed. An optimal matching formulation is then developed to derive the M&A solutions based on the obtained matching degrees. The proposed InvDEA model for assessing technical efficiency has the following merits: 1) it has a clear modeling mechanism that measures the maximum possible outputs by consuming the merged inputs; 2) the model can easily be extended under the different assumption of RTS; 3) the given relative efficiency can be reassigned according to a real situation. Also, the scale efficiency derived by the conventional DEA model not only can identify the type of RTS, but also can be well integrated with the technical efficiency. The developed approach was demonstrated with a practical example of 20 energy firms in Turkey. Comparative analysis revealed that using the above two kinds of efficiencies together can result in a feasible matching solution. The present study can not only shed light on the performance improvement in M&A matching decision but also extend the application scope of InvDEA approach. Nevertheless, there are some weak points in this research. Firstly, we simply suppose the given efficiency scores of each DMU are efficient in model (4), yet the scores may be adjusted according to a practical situation. Also, the case study is merely conducted under a small amount of data. For future studies, one worthwhile research direction is to investigate the DEA-based approach with undesirable outputs since environmental protection has been a broad industry consensus; another direction is to extend the M&A matching into many-to-one (or many-to-many) scenario.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This work is supported by the National Social Science Foundation of China (19BGL092).

References

Akkus, O., Cookson, J. A., & Hortacsu, A. (2016). The determinants of bank mergers: A revealed preference analysis. *Management Science*, *62*(8), 2241–2258. https://doi.org/10.1287/mnsc.2015.2245

Amin, G. R., & Oukil, A. (2019). Flexible target setting in mergers using inverse data envelopment analysis. *International Journal of Operational Research*, *35*(3), 301–317. https://doi.org/10.1504/IJOR.2019.10022710

Amin, G. R., Al-Muharrami, S., & Toloo, M. (2019). A combined goal programming and inverse DEA method for target setting in mergers. *Expert Systems with Applications*, *115*, 412–417. https://doi.org/10.1016/j.eswa.2018.08.018

Azevedo, E. M. (2014). Imperfect competition in two-sided matching markets. *Games and Economic Behavior*, *83*, 207–223. https://doi.org/10.1016/j.geb.2013.11.009

Banker, R. D. (1984). Estimating most productive scale size using data envelopment analysis. *European Journal of Operational Research*, *17*(1), 35–44. https://doi.org/10.1016/0377-2217(84)90006-7

Banker, R. D., & Thrall, R. M. (1992). Estimation of returns to scale using data envelopment analysis. *European Journal of Operational Research*, *62*(1), 74–84. https://doi.org/10.1016/0377-2217(92)90178-C

Bando, K., Kawasaki, R., & Muto, S. (2016). Two-sided matching with externalities: A survey. *Journal of the Operations Research Society of Japan*, *59*(1), 35–71. https://doi.org/10.15807/jorsj.59.35

Bogetoft, P., & Wang, D. (2005). Estimating the potential gains from mergers. *Journal of Productivity Analysis*, *23*(2), 145–171. https://doi.org/10.1007/s11123-005-1326-7

Braguinsky, S., Ohyama, A., Okazaki, T., & Syverson, C. (2015). Acquisitions, productivity, and profitability: Evidence from the Japanese cotton spinning industry. *American Economic Review*, *105*(7), 2086–2119. https://doi.org/10.1257/aer.20140150

Capron, L., & Pistre, N. (2002). When do acquirers earn abnormal returns. *Strategic Management Journal*, *23*(9), 781–794. https://doi.org/10.1002/smj.262

Cartwright, S. & Schoenberg, R. (2006). Thirty years of mergers and acquisitions research: Recent advances and future opportunities. *British journal of management*, *17*(S1): 1–5. https://doi.org/10.1111/j.1467-8551.2006.00475.x

Cartwright, S., & Cooper, C. L. (1993). The psychological impact of merger and acquisition on the individual: A study of building society managers. *Human Relations*, *46*(3), 327–347. https://doi.org/10.1177/001872679304600302

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, *2*(6), 429–444. https://doi.org/10.1016/0377-2217(78)90138-8

Chanmugam, R., Shill, W., Mann, D., Ficery, K., & Pursche, B. (2005). The intelligent clean room: Ensuring value capture in mergers and acquisitions. *Journal of Business Strategy*, *26*(3), 43–49. https://doi.org/10.1108/02756660510597092

Chen, Z., Wanke, P., & Tsionas, M. G. (2018). Assessing the strategic fit of potential M&As in Chinese banking: A novel Bayesian stochastic frontier approach. *Economic Modelling*, *73*, 254–263.

Chen, L., Wang, Y., Lai, F., & Feng, F. (2017). An investment analysis for China's sustainable development based on inverse data envelopment analysis. *Journal of Cleaner Production*, *142*, 1638–1649. https://doi.org/10.1016/j.jclepro.2016.11.129

Cook, W. D., & Seiford, L. M. (2009). Data envelopment analysis (DEA)-thirty years on. *European Journal of Operational Research*, *192*(1), 1–17. https://doi.org/10.1016/j.ejor.2008.01.032

DeYoung, R., Evanoff, D. D., & Molyneux, P. (2009). Mergers and acquisitions of financial institutions: A review of the post-2000 literature. *Journal of Financial Services Research*, *36*(2/3), 87–110. https://doi.org/10.1007/s10693-009-0066-7

Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society: Series A (General)*, *120*(3), 253–281. https://doi.org/10.2307/2343100

Gale, D., & Shapley, L. S. (1962). College admissions and the stability of marriage. *The American Mathematical Monthly*, *69*(1), 9–15. https://doi.org/10.2307/2312726

Gattoufi, S., Amin, G. R., & Emrouznejad, A. (2014). A new inverse DEA method for merging banks. *IMA Journal of Management Mathematics*, *25*(1), 73–87. https://doi.org/10.1093/imaman/dps027

Ghiyasi, M. (2015). On inverse DEA model: The case of variable returns to scale. *Computers & Industrial Engineering*, *87*, 407–409. https://doi.org/10.1016/j.cie.2015.05.018

Halkos, G. E., & Tzeremes, N. G. (2013). Estimating the degree of operating efficiency gains from a potential bank merger and acquisition: A DEA bootstrapped approach. *Journal of Banking & Finance*, *37*(5), 1658–1668. https://doi.org/10.1016/j.jbankfin.2012.12.009

Hadi-Vencheh, A., Foroughi, A. A., & Soleimani-Damaneh, M. (2008). A DEA model for resource allocation. *Economic Modelling*, *25*(5), 983–993. https://doi.org/10.1016/j.econmod.2008.01.003

Kristensen, T., Bogetoft, P., & Pedersen, K. M. (2010). Potential gains from hospital mergers in Denmark. *Health Care Management Science*, *13*(4), 334–345. https://doi.org/10.1007/s10729-010-9133-8

Jahanshahloo, G. R., Soleimani-Damaneh, M., & Ghobadi, S. (2015). Inverse DEA under inter-temporal dependence using multiple-objective programming. *European Journal of Operational Research*, *240*(2), 447–456. https://doi.org/10.1016/j.ejor.2014.07.002

Jiang, Z. Z., Ip, W. H., Lau, H. C., & Fan, Z. P. (2011). Multi-objective optimization matching for one-shot multi-attribute exchanges with quantity discounts in E-brokerage. *Expert Systems with Applications*, *38*(4), 4169–4180. https://doi.org/10.1016/j.eswa.2010.09.079

Le, D. T., Zhang, M., & Ren, F. (2018). An economic model-based matching approach between buyers and sellers through a broker in an open e-marketplace. *Journal of Systems Science and Systems Engineering*, *27*(2), 156–179. https://doi.org/10.1007/s11518-018-5362-z

Liang, L., Wu, J., Cook, W. D., & Zhu, J. (2008). The DEA game cross-efficiency model and its Nash equilibrium. *Operations Research*, *56*(5), 1278–1288. https://doi.org/10.1287/opre.1070.0487

Lin, Y., Wang, Y. M., & Chin, K. S. (2019a). An enhanced approach for two-sided matching with 2-tuple linguistic multi-attribute preference. *Soft Computing*, *23*(17), 7977–7990. https://doi.org/10.1007/s00500-018-3436-y

Lin, Y., Yan, L., & Wang, Y. M. (2019b). Performance evaluation and investment analysis for container port sustainable development in china: An inverse DEA approach. *Sustainability*, *11*(17), 4617. https://doi.org/10.3390/su11174617

Okumura, Y. (2017). A one-sided many-to-many matching problem. *Journal of Mathematical Economics*, *72*, 104–111. https://doi.org/10.1016/j.jmateco.2017.07.006

Önüt, S., & Soner, S. (2007). Analysis of energy use and efficiency in Turkish manufacturing sector SMEs. *Energy Conversion and Management*, *48*(2), 384–394. https://doi.org/10.1016/j.enconman.2006.07.009

Park, M. (2013). Understanding merger incentives and outcomes in the US mutual fund industry. *Journal of Banking & Finance*, *37*(11), 4368–4380.

Qian, J. Q., & Zhu, J. L. (2018). Return to invested capital and the performance of mergers and acquisitions. *Management Science*, *64*(10), 4818–4834. https://doi.org/10.1287/mnsc.2017.2766

Rahman, M., Lambkin, M., & Hussain, D. (2016). Value creation and appropriation following M&A: A data envelopment analysis. *Journal of Business Research*, *69*(12), 5628–5635. https://doi.org/10.1016/j.jbusres.2016.03.070

Roth, A. E. (1982). The economics of matching: Stability and incentives. *Mathematics of Operations Research*, *7*(4), 617–628. https://doi.org/10.1287/moor.7.4.617

Roth, A. E., & Sotomayor, M. (1992). Two-sided matching. *Handbook of Game Theory with Economic Applications*, *1*, 485–541.

Salter, M. S., & Weinhold, W. A. (1979). *Diversification through acquisition: Strategies for creating economic value*. The Free Press.

Shi, H. L., Wang, Y. M., Chen, S. Q., & Lan, Y. X. (2017). An approach to two-sided M&A fits based on a cross-efficiency evaluation with contrasting attitudes. *Journal of the Operational Research Society*, *68*(1), 41–52.

Shi, X., Li, Y., Emrouznejad, A., Xie, J., & Liang, L. (2017). Estimation of potential gains from bank mergers: A novel two-stage cost efficiency DEA model. *Journal of the Operational Research Society*, *68*(9), 1045–1055. https://doi.org/10.1057/s41274-016-0106-2

Sørensen, M. (2007). How smart is smart money? A two-sided matching model of venture capital. *The Journal of Finance*, *62*(6), 2725–2762. https://doi.org/10.1111/j.1540-6261.2007.01291.x

Steigenberger, N. (2017). The challenge of integration: A review of the M&A integration literature. *International Journal of Management Reviews*, *19*(4), 408–431.

SufianMajid, M. Z. A. (2007). Deregulation, consolidation and banks efficiency in Singapore: Evidence from event study window approach and Tobit analysis. *International Review of Economics*, *54*(2), 261–283. https://doi.org/10.1007/s12232-007-0017-2

Tsai, W. (2000). Social capital, strategic relatedness and the formation of intraorganizational linkages. *Strategic Management Journal*, *21*(9), 925–939. https://doi.org/10.1002/1097-0266(200009)21:9<925::AID-SMJ129>3.0.CO;2-I

Vizcaíno-González, M., & Navío-Marco, J. (2018). Influence of shareholders' support over mergers and acquisitions in US banks. *Economic Research-Ekonomska Istraživanja*, *31*(1), 228–239. https://doi.org/10.1080/1331677X.2018.1429296

Wang, Y. M., Fan, Z. P., & Hua, Z. (2007). A chi-square method for obtaining a priority vector from multiplicative and fuzzy preference relations. *European Journal of Operational Research*, *182*(1), 356–366. https://doi.org/10.1016/j.ejor.2006.07.020

Wang, Y. M., & Chin, K. S. (2010). A neutral DEA model for cross-efficiency evaluation and its extension. *Expert Systems with Applications*, *37*(5), 3666–3675. https://doi.org/10.1016/j.eswa.2009.10.024

Wang, Y. M., & Luo, Y. (2010). Integration of correlations with standard deviations for determining attribute weights in multiple attribute decision making. *Mathematical and Computer Modelling*, *51*(1–2), 1–12. https://doi.org/10.1016/j.mcm.2009.07.016

Wanke, P., Azad, M. A. K., & Correa, H. (2019). Mergers and acquisitions strategic fit in Middle Eastern banking: An NDEA approach. *International Journal of Services and Operations Management*, *33*(1), 1–25. https://doi.org/10.1504/IJSOM.2019.099652

Wei, Q., Zhang, J., & Zhang, X. (2000). An inverse DEA model for inputs/outputs estimate. *European Journal of Operational Research*, *121*(1), 151–163. https://doi.org/10.1016/S0377-2217(99)00007-7

Wernerfelt, B. (1995). The resource-based view of the firm: Ten years after. *Strategic Management Journal*, *16*(3), 171–174. https://doi.org/10.1002/smj.4250160303

Xu, Y., Patnayakuni, R., & Wang, H. (2013). Logarithmic least squares method to priority for group decision making with incomplete fuzzy preference relations. *Applied Mathematical Modelling*, *37*(4), 2139–2152. https://doi.org/10.1016/j.apm.2012.05.010

Yang, G. L., Rousseau, R., Yang, L. Y., & Liu, W. B. (2014). A study on directional returns to scale. *Journal of Informetrics*, *8*(3), 628–641. https://doi.org/10.1016/j.joi.2014.05.004

Yannick, G. Z. S., Zhao, H., & Belinga, T. (2016). Technical efficiency assessment using data envelopment analysis: an application to the banking sector of Cote d'Ivoire. *Procedia Social and Behavioral Sciences*, *235*(2016), 198–207. https://doi.org/10.1016/j.sbspro.2016.11.015

Zheng, S., Lam, C. M., Hsu, S. C., & Ren, J. (2018). Evaluating efficiency of energy conservation measures in energy service companies in China. *Energy Policy*, *122*, 580–591. https://doi.org/10.1016/j.enpol.2018.08.011