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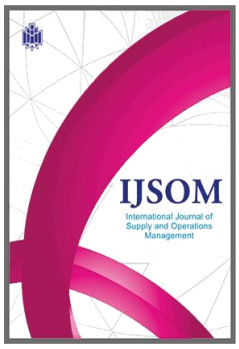

Credit Rating of Commercial Companies Using Data Envelopment Analysis (DEA) Model: A Case Study of 100 Iranian Active Commercial Companies in Import

Mehdi Fesanghari [a], Mariam Ameli [a*] and Hamidreza Izadbakhsh [a]

[a] *Department of Industrial Engineering, Faculty of Engineering, Kharazmi University, Tehran, Iran*

Abstract

One of the important issues in Iran is to monitor imports and business processes as well as exchange rates. Given the government's supportive policies for traders, how to implement these policies is challenging. An strategy to implement targeted oversight and policies is to control the actions of active traders based on their background. Data Envelopment Analysis (DEA) is one of the key tools to achieve this goal. The present research is based on Slack-Based Measure DEA Model (SBM-DEA) with an output-based approach which rates traders using real data as well as their background. In this model, 30 input indicators and six output indicators were first considered. Subsequently, given the correlation between them, the number was reduced to five input and four output indicators. After the extraction of effective input and output indicators, traders' efficiency was measured and rated using DEA model. Then, well-respected traders would receive facilities and various supports. To evaluate the performance of the model, the traders also were ranked using the Best Worst Method (BWM and after results shows better performance of the DEA model. Another result and application is the use of reference decision-making units, who indicate traders that are expected to have good performance by the market knowledge. Recognizing these units allows policy-makers to reduce other traders' risk by disseminating their behavior. Another important application is traders' classifications. By knowing the traders, the policy-maker reference can make a good classification of them, which is necessary for different resource allocation or facilitating policies.

Keywords: Data Envelopment Analysis (DEA); Slack Based Measure DEA Model; Best Worst Method (BWM); Trader; Rating, Efficiency.

1. Introduction

Based on the World Bank ranking, Iran is ranked 127 out of 190 countries in the world based on ease of doing business index. This report indicates the critical situation of Iran in business ease. On the other hand, due to the imposition of various sanctions against Iran and the severe shortage of foreign exchange resources in the country, it is necessary to determine the amount of foreign exchange that can be allocated to each enterprise using various monitoring tools to prevent waste of existing resources.

At present, the lack of proper systems for measuring and evaluating the performance of individuals has led to the creation of long and complex processes, so that the amount of risk of each person during long and complex processes is identified. Ranking is one of the best tools that leads to assess risk and performance of individuals, in

*Corresponding author email address: m.ameli@khu.ac.ir
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addition to facilitating business. Consequently, the government can assess the status of each business and allocate foreign exchange or other support based on it.

The credit rating concept has originated in the United States; today, 100% of bonds and bond issuer companies are rated in the United States, and credit rating agencies have been established in many countries to serve the investors and creditors (Kumar and Hayne, 2003). Credit rating is done by credit rating agencies. It is generally conducted in three areas: first, analyzing whether the credit rating measures what it claims, i.e., the credit of company, or not, second, investigating credit rating information content in the capital market, and third, specifying the rating determinants (Matthies, 2013).

By accurately defining the ranking indicators, a complete knowledge of the ranked units is obtained and the ability of comparing the strengths and weaknesses of the units is provided. Accordingly, the government will be able to make policies and determine incentives or restrictions based on appropriate criteria for individuals (natural and legal). This study seeks to rank commercial companies based on performance records and the degree of adherence to government obligations (foreign exchange liability, foreign exchange return, tax debt, etc.). So, first determine the areas related to performance records and related indicators. Then, after collecting merchants' data, the ranking is done using the Data Envelopment Method (DEM) and the best-worst method, and then the results of both models are reviewed.

In this regard, the rest of the paper is organized as follows. Theoretical foundations and background of the study are presented in section 2. Research method including problem statement, model resolution and results are described in Section 3. The performance evaluation and sensitivity analysis of the model are provided in section 4. Finally, section 5 concludes the paper and provides suggestions for future research.

2. Theoretical Foundations and Research Background

Performance evaluation of different stakeholders was always a critical and challenging issue for decision makers in many areas like supplier evaluation and selection or evaluating and ranking branches and units under supervision, e.g., (Ersoy and Dogan, 2020), (Rahiminezhad Galankashi et al., 2023), (Forghani et al., 2022).

DEA is one of the main approaches introduced and developed to rank businesses, and it is a concept of calculating the efficiency of each unit compared to some units with the most efficiency (Haas et al., 2004). This method is based on a linear programming approach whose main objective is to compare and evaluate the efficiency of a number of similar decision-making units with different number of inputs and outputs (Banker et al., 1986). The first DEA model was named CCR based on the names of its developers. In 1984, by changing the CCR model, Banker, Charnes, and Cooper proposed a new model as several models for technical estimation and efficiency assessment using DEA method became known as the BCC based on their names' first letter. It is a DEA model evaluating the relative efficiency of units with variable return in proportion to scale (Banker et al., 1984).

Generally, DEA patterns are divided into two categories of input-based and output-based. The input-based procedure means the outputs are kept constant that in the model, and the inputs are reduced, and the output-based procedure refers to keeping the inputs constant and increasing the outputs. Two types of DEA are known in the DEA area: radial and non-radial. Radial models introduced by the CCR model are based on relative input and output changes. On the other hand, non-radial models like SBM models directly deal with the slack variables of inputs and outputs and do not deal with the relative changes of inputs and outputs.

CCR scores indicate the amount that must be deducted (added) from (to) the inputs (to outputs). However, in real-world issues, not all inputs or outputs behave relatively. For example, some of inputs such as workforce, materials, and financial resources are replaceable and relatively unchanged. Another disadvantage of radial models is the lack of considering slacks in reporting the effectiveness score, however, if these slacks are not observed, the radial approach will present misleading decisions.

Contrary to the above, Slack-Based Measure (SBM) models do not consider assumptions about relative changes in inputs and outputs. Indeed, SBM models do not handle input/output slacks directly, and do not assume proportional changes of inputs or outputs. SBM models are designed to meet the following two conditions:

I) Constant units: measurement must be constant given the data units

II) Monotone: measurement should be monotone given the input and output slacks.

Table 1. The notation of the SBM model

Sets and Indexes
$i \in \{1,2,\dots,m\}$: Index related to the Input,
$j \in \{1,2,\dots,n\}$: Index related to the DMUs,
$r \in \{1,2,\dots,s\}$: Index related to the Output,
$o \in \{1,2,\dots,n\}$: Index related to the Period.
Parameters
y_{rj}: The output r for DMU j,
x_{ij}: The input i for DMU j.
Variable
λ_j: the intensity DMU j,
s_i^-: Slack of the input i,
s_r^+: Slack of the output j,
ρ_o^* : efficiency of DMU in period o ($A\ DMU_o = (x_o, y_o)$ is called efficient if $\rho_o^* = 1$ holds),
y_{ro}: The output r for DMU_o,
x_{io}: The input i for DMU_o.

The SBM model was introduced by Tone (2001). This model has three variants: input-based, output-based, no orientation. No orientation model affects both input and output simultaneously. This model is expressed as mathematical equations as follows, where the notation of the SBM model is presented in Table 1. If we consider X as the set of inputs with n DMUs and m inputs, and Y as the outputs vector with s outputs, then
$\mathrm{X} = (x_1, x_2 \dots, x_n) \in R^{m\times n}$ *and* $Y = (y_1, y_2 \dots, y_n) \in R^{m\times n}$ and if $X > 0$ and $Y > 0$.

The production capability set will be as follows:

$$\mathrm{P} = \left\{(\mathrm{x},\mathrm{y})\ \mathrm{x} \geq \sum_{j=1}^{n} \lambda_i\ x_j,\ 0 \leq \mathrm{y} \leq \sum_{j=1}^{n} \lambda_i\ x_j\ , \lambda \geq 0\right\} \quad (1)$$

where λ variable is called the intensity vector: $\lambda = (\lambda_1, \lambda_2 \dots, \lambda_n)^T$. The inequalities with the slack variable become as:

$$x = \sum_{j=1}^{n} \lambda_j\, x_j + s^-\ , \qquad y = \sum_{j=1}^{n} \lambda_j\, x_j - s^+, \qquad s^- \geq 0\ ,\ s^+ \geq 0. \quad (2)$$

Given the nature of the model required in this research in the assessment of the efficiency, and that the model should be applied as output-based form, the output-based SBM model is as follows (Cooper et al., 2011):

$$\frac{1}{\rho_0^*} = max_{\lambda, s^-, s^+}\ 1 + \frac{1}{s} \sum_{r=1}^{s} \frac{s_r^+}{y_{ro}} \quad (3)$$

subject to

$$x_{io} = \sum_{j=1}^{n} x_{ij}\, \lambda_j + s_i^- \quad (i = 1 \dots \dots . m), \quad (4)$$
$$y_{ro} = \sum_{j=1}^{n} y_{ij}\, \lambda_j + s_r^+ \quad (i = 1 \dots \dots . s), \quad (5)$$
$$\lambda_j \geq 0\ (\forall_j),\ s_i^- \geq 0(\forall_j), s_r^+ \geq 0(\forall_r). \quad (6)$$

One of the problems with assessing the efficiency of DMUs is how to deal with the undesirable outputs produced jointly with the desirable outputs (Guo and Wu, 2013). In traditional literature, only the desired output value is considered and the undesirable output is simply ignored. Ignoring the undesirable output equals, the saying that they have no impact on the final assessment and this can produce wrong results. New assessments also consider undesirable outputs. Significant research has been done by considering undesirable outputs in the DEA method, some of which and a review of the literature in the field relevant to the present discussion will be referred to.

Bovilaciva and Braglia have introduced a new model for the (relative) assessment of the environmental bio-efficiency of the Italian oil refineries in the paper "Environmental Bio-efficiency of the Italian Oil Refineries" (Bevilacqua and Braglia, 2002).

There are several different methods to include undesirable outputs into the model. The simplest one is to treat the undesirable good as an input. Some papers taken this approach and provided more justification for it include Mandal and Madheswaran (2009), Carper and Oates (1992), Coop (2008), Reinhard (1999) and Reinhard et al. (1999). Using DEA, Ali Heydari et al. (2015) examined a model for rating active companies operating in different industries, applying for banking facilities. Faghih and Askarifar (2014) used input oriented CCR, output oriented BCC and SBM-DEA to rank 57 countries according to their national innovation capacity improvement. Their results indicate the superiority of SBM-DEA over other approaches.

Khezrimotlaq et al. (2019) in their study have analyzed DEA in macro data. In this paper, they express that with the use of DEA, the resolution duration is increasingly enhanced by increasing the number of decision-making units. Through designing a 5-step framework and implementing it on about 30,000 real data, they concluded that the designed model had considerably reduced the model resolution duration. Zhu et al. applied DEA based approach in the big data context for Efficiency evaluation (Zhu et al., 2018). Henriques et al. (2023) used a base point SBM approach which permits for negative data to evaluate the performance of Us and European exchange traded funds. Alves and Meza (2023) provided a systematic review on SBM for network DEA models which can shed light on the wide range of applications of SBM.

Investigation of the current state of the country indicates that one of the key issues the country faced at present is currency and its management. One of the most prominent applications of currency is its use in the import of various materials. Lack of a model for credit rating of trader and importers in the country will result in widespread tax evasion (more than 5 trillion Tomans by the end of the year 1396 (solar year), according to official tax statistics), failure to pay customs duties (debt over one trillion Tomans to the custom duty system based on the documented data recorded in Asycuda System) and other relevant corruption.

Hashem Abadi (2005) evaluated the efficiency and productivity in some Iranian oil refineries using data analysis.

Rashidi and Cullinane (2019) evaluated the sustainability of operational logistics performance in comparison with the Logistics Performance Index (LPI). DEA is applied to derive an efficiency score reflecting the degree to which sustainable operational logistics performance (SOLP) is achieved within each sample nation.

Khezrimotlaq and Chen (2018) have mentioned that the DEA Model is suitable on measuring the performance of a set of homogenous firms with multiple input factors and multiple output factors. Rezaeian and Foroughi (2018) have used the rational analysis and DEA to rank the impact of efficient DMUs to evaluate the inefficient DMUs. Their new approach has the capability for ranking extreme and non-extreme efficient DMUs. Further, it has no problem in dealing with negative data. Izadikhah and Saen (2020) have present a new DEA model for ranking DMUs (suppliers) based on a modification of context dependent DEA models. according to the literature review they believed that one of the important ways for evaluating sustainable suppliers is to use DEA models. Sadeghi et al. (2023) applied modified SBM as an efficiency measurement method in order to evaluate the performance of Iranian insurance companies. They tried to achieve managerial insight on the dual effect of marketing and profit creation in the three periods of 1396 to 1398.

It is obvious that credit rating of economic activists, especially traders, and its use in various bottlenecks, such as imports, is one of the best strategies to prevent trade card-related corruption; thus, the need for a credit rating model for traders is increasingly felt in assessing the extent to which traders' commitments to the country's future planning are fulfilled. Obviously, the international trade interactions are of great importance to the economy of the country, and accordingly, the country has long been trying to increase customs with pathway choice and custom clearance just based on what the traders announce.

On the other hand, in addition to all costs of purchasing, shipping, insurance, entrance fees, etc., imposing additional costs such as import tax on all traders in this status of the country's economy is one of the serious problems of working capitalists. The only way to prevent the aforementioned offenses and corruption is to distinguish honest traders from a few offender ones, which is not possible without credit rating. In the present study, it has been tried to

aggregate and select indices related to credit rating of traders through studying the existing literature in the field of ratings and considering the existing data in the country, and then weight and finally calculate the credit rating of each trader by DEA model.

3. Problem Statement and Research Method

Considering that it is necessary to have a business card to do business in Iran, the target population of this study is all merchants who have a valid business card and have done import or export process at least once. The steps performed in the research are as follows.

I) Inputs and outputs identification

After determining the target community, first the areas related to performance records in both business and financial areas were determined through a library survey, then through interviews with experts, the indicators of each area were determined and all indicators of these two areas were considered as input. Output indicators were also determined using the opinion of experts and with the aim of assessing the extent to which the merchant fulfills governmental obligations.

II) Data collection

The indicators determined in terms of the existence of the database were divided into two categories: with\without a valid information reference. Due to the volume of required information and the impossibility of collecting data, indicators without information reference were removed or the nearest index with information reference was replaced. With this process, ranking indicators were calculated and then traders' information was inquired from relevant authorities.

III) Data cleaning

The data was first purified and then each of the indicators was calculated per company. In the second step, traders whose data was incomplete or out of the ordinary range were removed (the normal range was determined by an expert and indicates which reference data is incorrect).

IV) Statistical sample selection

In this step, the statistical sample was selected from the multi-stage cluster sampling method. At first, the merchants were identified separately for each province, then a total of 100 samples were randomly selected according to the number of business cards in that province. Then, state-owned ones were eliminated and a company from the province similar to the eliminated one was replaced. Figure 1 shows the process of reaching 100 companies to implement the ranking.

Table 2. Indicators of financial status

Descriptions	Indicator	Area
(Total Current Assets) / (Total Current Debts)	Current Ratio	Liquidity ratios
(Total Current Cash Assets) / (Total Current Debts)	Cash ratio	
(Total Debts) / (Total Assets)	Debt ratio	Leverage ratios
(Operating income) / (Average total assets at the beginning and end of the period)	Total turnover ratio of assets	Activity ratios

This research is done on real information and the extracted model can be used to rank traders. Considering the importance of companies' financial issues in fulfilling governmental obligations, also financial indicators have been selected for use in the model. Financial indicators have been obtained from 100 selected companies in cooperation with them, according to Table 2.

Table 3. Output indicators of the proposed model

1	Ratio of total tax offences to definitive/diagnosis tax
2	Ratio of tax debt to payable tax
3	Ration of total currency commitment elimination to the total received currency
4	Ratio of expressed tax to definitive/diagnosis tax

The import rate index of the company in the past year is considered as an input index as well as those in in Table 2. Table 3. presents the output of the model regarding the objective of the study (i.e., to investigate and assess the amount of debts of traders owed to the government) and the ranking based on the efficiency of the traders in repaying their obligations to the government.

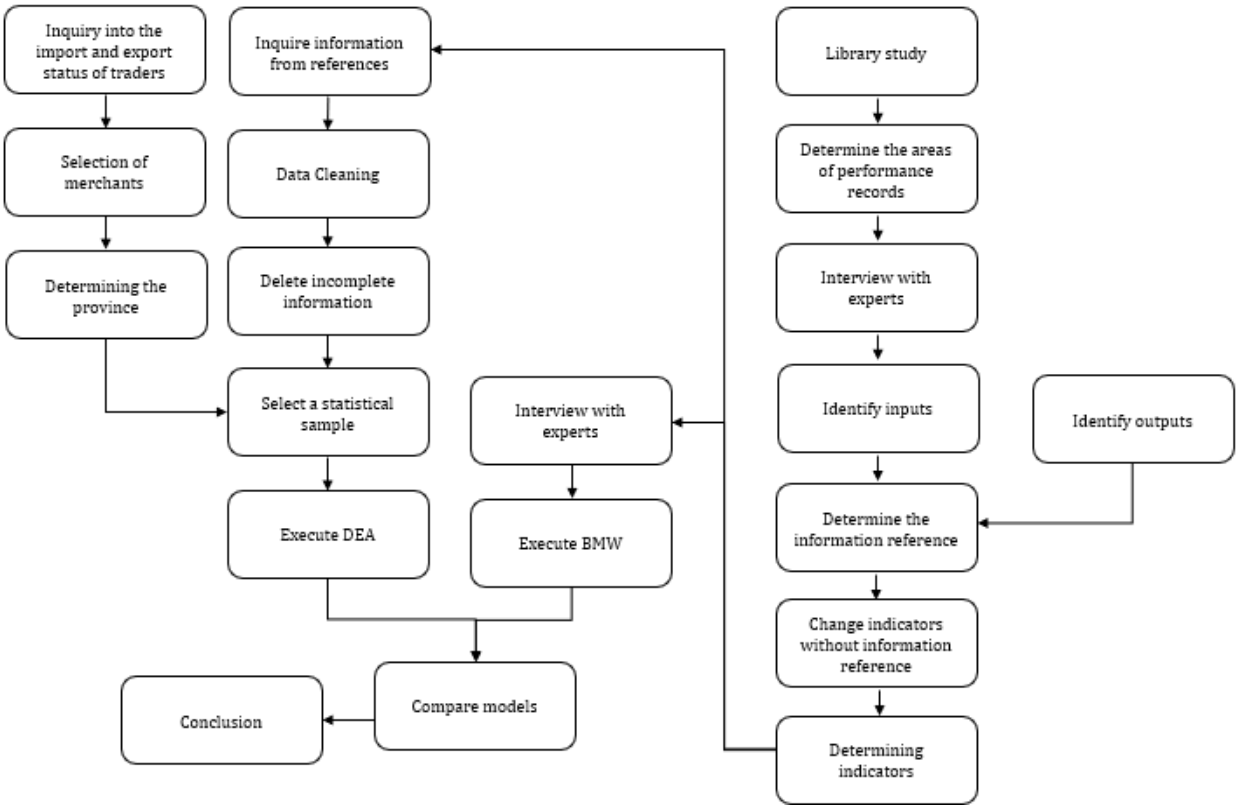

Figure 1. The process of selecting 100 companies.

3.1. Model Resolution

One of the basic conditions for using DEA is the absence of negative values in the data. Given the presence of negative data in some indices, the data were re-examined to eliminate this problem. Since the indices with negative data are of the numerical indices rather than the ratio, a constant value was added to the data to eliminate the problem of negative values while keeping the relative number spacing.

Table 4. Input indicators of the proposed model

Import	Total turnover ratio of assets	Debt Ratio	Cash Ratio	Current Ratio	DMUs
123180	0.642	7.773	0.128	6.562	1
215000	10.029	9.119	1.573	9.343	2
5276940	17.067	7.424	0.384	14.25	3
3680110	12.893	6.795	4.089	24.892	4
3092130	3.892	9.129	0.054	9.507	5
8964720	4.517	11.274	0.189	6.094	6
722970	3.6	7.184	0.32	14.068	7
7477640	9.682	9.004	0.671	9.682	8
2177320	4.599	7.218	0.849	20.305	9
2538720	9.369	8.363	0.23	12.481	10
5500100	3.786	7.158	0.336	11.917	11
1737210	1.556	7.572	0.076	5.398	12
2397140	9.189	6.756	0.682	19.751	13
2498420	10.113	7.247	0.159	10.222	14
765300	6.808	6.949	0.535	7.912	15
756680	11.016	8.08	1.278	37.538	16
4136370	7.713	5.386	1.207	21.191	17
1013250	6.777	6.952	1.093	11.953	18
1139650	20.903	7.488	13.396	77.221	19
2316000	5.152	8.379	0.576	11.754	20
7773530	3.222	9.218	0.041	4.472	21
5425470	9.664	5.278	0.907	15.479	22
806990	11.437	7.892	0.122	11.862	23
168750	2.442	5.65	0.308	17.861	24
729120	2.753	9.562	0.183	9.497	25

Since the data were real and the principle of data confidentiality had to be preserved, all data were multiplied by a specific coefficient and were used in calculations. Another problem with calculation of the efficiency of DMUs was the correlation between some of the input indicators. By calculating the correlation coefficients for each index, the indices with correlation were specified. After specifying the indices, the question is which of the indices with correlation should be eliminated and which ones selected. In this regard, if one of the indices correlated with another one is eliminated in the set of input indices of the DEA approach, considerable effect will not be observed in the result. The model was solved by GAMS (version: 25.0.2) using the Barron solver and are executed on a PC with 4-GB RAM and 2.53-GHz CPU. In Table 4, the input indicators are initially presented and then in the Table 5 the output indicators are listed.

Table 5. Output indicators of the proposed model

Declarative Tax	Currency Liabilities	Tax Debt	Tax Penalty	Ratio/DMUs
24.1	1000.1	886	329.8	1
105.4	1000.1	387.9	48.3	2
51.5	1000.1	7.5	6.1	3
18	1590.8	494.4	241.5	4
191.4	1000.1	112.8	27.2	5
70.2	1112.5	261.5	10.2	6
230.1	1000.1	483.2	98.1	7
160.1	1076.4	604.2	218.6	8
43.7	1002.6	7.1	10.4	9
167.3	1000.1	450.3	3.3	10
167.9	1000.1	498.1	39.8	11
39.6	1048.3	266.7	55.6	12
71.7	1071.1	642.4	41	13
257.1	1000.1	54.7	23	14
32.7	1000.1	597.1	16.5	15
71.8	1000.1	352.3	14.3	16
738.5	1205.2	246.2	198.5	17
214	1152.6	591.3	4.2	18
52.7	1085.4	516.1	4	19
276.1	1000.1	218.9	18.6	20
56.2	1000.1	166.2	29.5	21
372.3	1000.1	105.9	97.9	22
15.6	1000.1	845.1	133.1	23
29.6	1000.1	225	56.2	24
135.6	1002	418.1	6	25

SBM-DEA was also tested with input-based and output-based scale. From the reasons for using this method, we can refer to the following: in slack-based DEA model, the target function is stable to unit change and the efficiency value does not vary by changing the input and output coefficients, i.e., if x_{ij} and y_{rj} are replaced by $k_j x_{ij}$ and $c_r y_{rj}$, respectively, the efficiency value will not change ($K\ and\ C\ > 0$). Moreover, the inputs surplus and output shortages of each DMU can be measured (Tone, 2001). This calculation helps in understanding the importance of each indicator in measuring efficiency. The value of each indicator can be calculated and assessed in future studies through using the proposed model, given that the purpose of ranking traders is to improve their behavior in the long term, in addition to above mentioned ones.

3.2. Results and Reference DMUs discussion

Illustrating reference DMUs is one of the outputs of the DEA method. Table 6 represents the results of implementing the proposed model. The units are traders who are expected to have good performance due to their market recognition. Recognizing these units helps policymakers to decline the risk of other traders by modeling these traders and disseminating their behavior. The significant point to note is considering the dimensions of the traders that is observed in this method, the model is appropriate for the medium-sized commerce (with a trading volume of $ 1 million per

year). Another key application of this output is the categorization of traders. This categorization can help policy-makers to decide very effectively. For instance, if government intends to increase liquidity of traders, it first should implement the new policy on reference traders. Then, after observing the resulting effects, predictions can be done on the percent of the target population which may be affected by implementing new policy.

Table 6. The Output of the proposed Model

DMUs	DEA	DMUs	DEA Score
1	1	11	0.22
2	0.32	12	0.24
3	0.02	13	0.27
4	0.11	14	0.11
5	0.14	15	0.12
6	0.04	16	0.09
7	0.56	17	1
8	0.54	18	0.05
9	0.03	19	0.02
10	0.02	20	0.08

4. Comparison of DEA model with SBM model

In order to evaluate the proposed model, the weight of each of the proposed indicators was extracted by the Best-Worst Method (BWM). BWM is one of the newest innovative methods in the field of MCDM and its benefits have been mentioned in various articles, e.g., (Tu, et al., 2023), (Vahabzadeh Najafi and Arshadi Khamseh, 2023), (Forghani, et al. 2022). Also, how to model and solve is presented in the article represented by Rezaei (2015). Accordingly, this method has been used in the present study.

The BWM is based on the opinion of experts, so the weight of the indicators is based on the opinions of four experts, including the Senior Government Director, one of the heads of unions, the Chief Executive Officer of the Chamber of Commerce and the University Expert. Weighting is done hierarchically first by dividing the proposed indicators into three categories: 1) Import 2) Output, which were the same output indicators of the proposed model in the DEA method, and 3) Financial indicators, which have already been fully defined. Experts' opinions are shown in Tables 7 and 8.

Table 7. Experts Opinions on ranking areas

Experts	Import	Financial	Output
Senior government director	31%	13%	56%
Heads of union	75%	9%	16%
Officer of chamber of commerce	66%	10%	24%
University expert	27%	17%	57%

After determining the categories, the indicators of the proposed model are weighted in each category and multiplied by the weight of each category to calculate the weight of the index. In the next step, all the values of the indices shown in Table 8 were became scale-less and projected to the interval [0,1]. Then, based on the weights calculated in the BWM, the score of each index for each DMU is calculated. By aggregating these scores, the position of each DMU is determined based on the total score received. Table 9 shows the score of 20 DMUs as an example.

Table 8. Experts Opinions on each of the ranking indicators

Experts/Ratio	Declarative tax	Currency Liabilities	Tax penalty	Tax Debt	turnover	Cash	Debt	Current
Senior government director	60%	10%	7%	24%	54%	8%	15%	23%
Heads of union	15%	8%	10%	68%	22%	7%	11%	59%
Officer of chamber of commerce	10%	13%	9%	68%	54%	8%	15%	23%
University expert	8%	14%	25%	53%	55%	6%	16%	23%

As shown in Table 9, DMUs get different scores based on the experts' point of view, and in some cases, there is significant difference between them. This discrepancy is due to the incomprehensive opinion of experts in all eras related to all the indicators. On the other hand, in the BWM method, the interaction of the indicators is assumed to be zero, which is not a real assumption. Figure 2 shows that the output of our proposed model is more in line with the opinions of experts than the BWM method. However, the opinions of the elites in general confirm the performance of the model. For example, DMU17 which was approved by the BWM and had a good performance based on all experts' opinions, obtained the efficiency of one in our proposed model too. So, the SBM-DEA model is more efficient and more reliable.

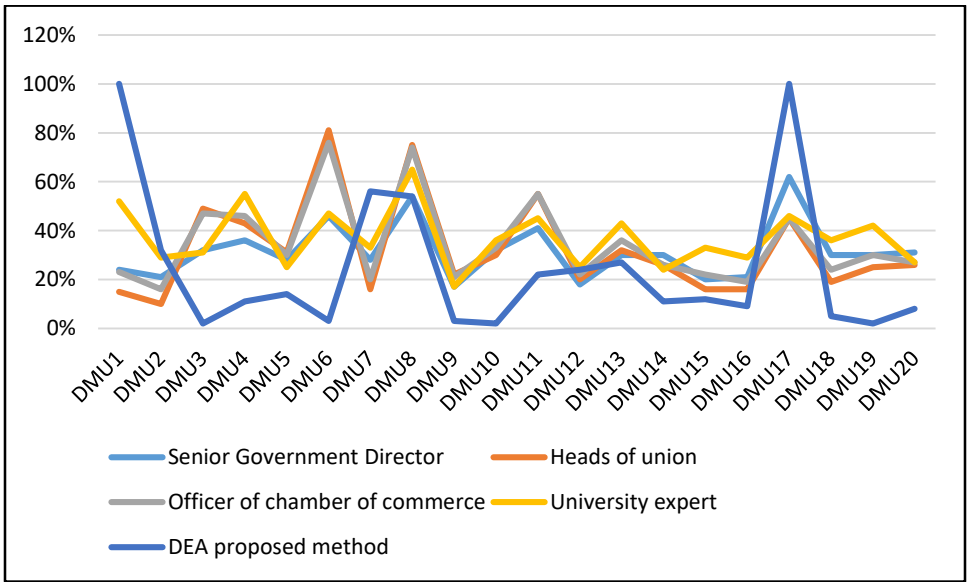

Figure 2. Comparison of proposed models results with expert opinions

Table 9. Scores of DMUs

DEA proposed method	University expert	Officer of chamber of commerce	Heads of union	Senior Government Director	DMUs
100%	52%	23%	15%	24%	1
32%	29%	16%	10%	21%	2
2%	31%	47%	49%	32%	3
11%	55%	46%	43%	36%	4
14%	25%	30%	31%	28%	5
3%	47%	76%	81%	46%	6
56%	33%	20%	16%	28%	7
54%	65%	74%	75%	54%	8
3%	17%	21%	22%	17%	9
2%	36%	33%	30%	32%	10
22%	45%	55%	55%	41%	11
24%	25%	22%	20%	18%	12
27%	43%	36%	32%	30%	13
11%	24%	26%	26%	30%	14
12%	33%	22%	16%	20%	15
9%	29%	19%	16%	21%	16
100%	46%	45%	45%	62%	17
5%	36%	24%	19%	30%	18
2%	42%	30%	25%	30%	19
8%	27%	27%	26%	31%	20

5. Conclusion

One of the government's key problems and challenges in Iran is monitoring traders' activities, controlling currency, and at the same time facilitating commercial processes to utilize the created opportunities and capabilities. In this paper, a real-life case study of 100 Iranian traders is studied using Slack-Based Measure Data Envelopment Analysis (SBM-DEA) model and the efficiency of these activists in the field of commerce was calculated and then were rated according to the calculated efficiencies. This ranking leads to the recognition of their behavior and allows for the allocation of governmental resources such as equipment and facilities to each trader based on their backgrounds. In addition to saving governmental resources and preventing waste of them, this facilitates the business process and provides the possibility to monitor the traders' activities.

The research was configured in two main stages. In the first stage, a research gap in the field of assessment of DMUs was identified which was the lack of a criterion for assessing and investigating the efficiency of traders. Then, based on the literature on the subject, besides the goal of rating (i.e., the assessment of the level of traders' adherence to their commitment to government), the output variables were identified and considered in the proposed model. Subsequently, the determined indicators were refined according to the correlation criterion and selected as the final input.

In the next step, 100 traders were assessed using the selected inputs and outputs by a non-parametric DEA approach. The efficiency of traders and commercial activists have always been one of the most important issues in the country and in recent years, its importance has been doubled given the policies adopted by the government to allocate government currency to traders and other subsidies and facilities considered for them. Moreover, it is obvious that international trade interactions are of paramount importance to the country's economy, and accordingly, the country

has long been trying to increase customs with pathway choice and custom clearance just based on what the traders announce. It is obvious that credit rating of economic activists, especially traders, and its use in various bottlenecks, such as imports, is one of the best strategies to prevent trade-related corruption; hence, the need for a credit rating model for traders is increasingly felt in assessing the extent to which traders' commitments to the country's future planning are fulfilled.

In the following, indicators related to traders' credit rating were extracted and then efficiency of each trader was measured by means of SBM-DEA method, based on which, the traders were rated. In order to evaluate the performance of the model, the proposed model was compared with BWM under the supervision of four experts and better performance of the proposed model was observed.

Recommendations for future research may include the use of parametric methods like regression analysis by which we can predict the predictor function of output behavior of each trader with different inputs. Furthermore, the Network Data Envelopment Analysis (NDEA) method can be employed to assess processes with sequences and analyze including components. In addition, the above framework that consists of data mining and DEA may also be used to assess other systems with the same objective, such as insurances and banks.

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