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The Influence of CCR/BCC Models and DEA Approach in Finding Branch Efficiency
A Case Study: EN-Bank

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Abstract

The purpose of this study was to illustrate a Data Envelopment Analysis (DEA) approach to assessing EN Bank branch network performance. In the present paper, we focused on deploying the DEA model to analyze bank branches' performance and which criteria could be selected as an input or output in developing the DEA model; of course, we concentrated on the suitable DEA models in Bank branch performance analysis. This paper used a two-stage Data Envelopment Analysis approach to simultaneously benchmark the bank branch's performance. After that, inputs and outputs were analyzed with CCR and BCC models to find branch efficiency. After analyzing the data, it can be concluded that BCC models are more optimistic. The average efficiency score and the number of efficient branches in BCC models for both approaches are more than the CCR model. The findings also indicated that the variation within branches in the intermediary model is more than the profitability model. This indicated that branches are more homogeneous in the profitability approach than the intermediary model. According to overall scores and ranking, we can compare the current EN bank score for each branch by its DEA overall score, and of course, their rank based on these scores can be supplied. Comparing them can lead the reader to find the compatibility of the current system by DEA ranking of branches.

Keywords: CCR/BCC models, DEA, Efficiency, Bank branch

INTRODUCTION

Banking is one of the most complex industries globally and a major contributor to a country's wealth. [8, 16, 17] Banks play a central role in the economy. [9] Today's banks offer a wide range of products and services, from simple checking accounts to retirement plans, mutual funds, home mortgages, consumer loans, and many others. The banks are forced to reevaluate what drives and how to improve the performance of bank branches. [11]

Many researchers have attempted to measure the productivity and efficiency of the banking industry using outputs, costs, efficiency, and performance. [2]

Estimating efficiency in the financial industry involves identifying the efficient frontier as a benchmark for measuring the relative performance of the units. The relative efficiency score of a banking organization is determined by how close it is to the efficient frontier. The methods of identifying the efficient frontier can be grouped in two broad categories: non-parametric and parametric. Non-parametric methods that include Data Envelopment Analysis (DEA) and Free Disposal Hull (FDH) do not restrict the functional form of the relationship between inputs and outputs. [11]

1.1. Techniques for measuring bank branch efficiency

There are numerous techniques used to measure bank branch operational efficiency. As one non-parametric frontier approach, DEA is an excellent and robust efficiency analysis tool with a broad range of applications. DEA was introduced by Charnes et al. [6] based on the work of Farrell. DEA has been demonstrated to be effective for benchmarking in many service industries involving complex input-output relationships

(Cooper et al., Zhu). In the last two decades, there have been numerous published applications of DEA to measure the efficiency of banks and branch systems, which have further motivated the development and improvement of DEA techniques. [14]

1.2. Sample Characteristics (EN Bank)

EN Bank is Iran's first private bank, established in 2001 by a consortium of industrial, construction, and investment companies, to provide flexible financial services to the burgeoning Iranian private sector.

For years, EN Bank has maintained its leadership position in providing innovative banking solutions, satisfying the banking needs of its rapidly expanding customer base while continuously guaranteeing significant shareholder returns. [15]

The main research aim here is to use the DEA model in Bank performance in Iran, which is developed by defining the customized profitability and intermediately models to the Iranian banking sector and combining the results in the SBM DEA model for the final ranking overall performance measure.

The authors use both CCR and BCC, DEA models in this study. And analyze all models mentioned above in CCR and BCC approach together. In the CCR model, return to scale is constant, which means that by increasing or decreasing the inputs, outputs proportionally increase or decrease with a constant rate. Still, in the BCC model, the rate of increase or decrease in outputs is not constant, which means that variation in outputs may be more or less in respect to variation in inputs.

2. Literature Review:

2.1. DEA Efficiency Analysis

DEA is a linear programming-based technique for evaluating the performance of productive units. It can handle multiple inputs and outputs instead of the other techniques such as ratio analysis or regression. [12]

Aly, Grabowski, Pasurka, and Rangan (1990) used the Charnes–Cooper–Rhodes (CCR) model to evaluate the technical efficiency, scale efficiency, and allocate efficiency of 322 independent USA banks in 1986. It is found that 35% of cost inefficiency was attributed to technical inefficiency, that is, input waste or use insufficiency was greater than input combination incorrectness, and technical inefficiency was due to pure technical efficiency slump but not scale inefficiency; a bank's scale in terms of total deposit or number of branches had a positive impact on pure technical efficiency. [13]

Elyasiani, Mehdian, and Rezvanian (1994) studied the survey of Federal Deposit Insurance Corporation on 203 commercial banks from 1983 to 1987; The result showed that production efficiency and financial efficiency had a significant correlation in most cases, indicating that the DEA measurement of a bank's production efficiency can serve as the reference for a bank's operator in doing financial analysis. [7]

Alirezaee, Howland, and van de Panne (1998) utilized data from 1282 bank branches in Canada to conduct numerical experiments relating to DEA results to sample size. They found that the average branch efficiency score varied inversely with the number of branches in the sample and directly with the total number of inputs and outputs. [3]

Avkiran (2011) investigates to what extent bank DEA super-efficiency estimates are associated with key financial ratios. A low correlation may present an opportunity to address inefficiencies that were not obvious in financial ratio analysis, thus enabling an update of inferences drawn from ratios. DEA can also objectively identify benchmarks for ratio analysis based on actual observed data collected from peers. Nine super-efficiency DEA formulations across two profitability models are systematically tested. [10]

2.2. Charnes–Cooper–Rhodes (CCR) model

Charnes, Cooper, and Rhodes (1978) [5] expanded Farrell's efficiency measurement concept of multiple inputs and single output to the concept of multiple inputs and multiple outputs, utilized linear combination to convert it to single virtual input and output, estimated efficiency frontier from the ratio of two linear combinations. They measured the relative efficiency of each DMU in CRS, which is between 0 and 1, and can determine whether a DMU is in constant, increasing, or decreasing returns to scale.[8]

2.3. Banker–Charnes–Cooper (BCC) model

Banker, Charnes, and Cooper (1984) widened the CCR model ratio concept and application scope in both Farrell and CCR models; efficiency was supposed to measure in CRS, but inefficiency might not have allocative efficiency, proper scale, and technical efficiency. In addition, Samoilenko and Osei-Bryson (2008) indicated that the DEA is a widely used non-parametric data analytic tool discriminatory power dependent on the homogeneity of the domain of the sample. [4]

2.4. The Production Model

The production approach measures how a branch produces transaction services (outputs) based on capital and labor (inputs). [8] The production approach, initiated by the contribution of Benston and Bell, and Murphy, describes banking activities as the production of services to depositors and borrowers. [1]

2.5. Input and Output variables

The inputs and outputs are measured in monetary units. The main important point in this process is that the input-output variables should be chosen following the type of efficiency being assessed (Sherman & Rupert, 2006). [9]

3. Methodology:

The Total Bank branches of EN Bank in the capital (Tehran) and Iran are 226. In this study, only Tehran branches were selected. One hundred seven branches are active in Tehran province. In this paper, because of the branch life, the existence of empty input and output, and accessibility of needed data, 50 branches were selected among the 98 branches of Tehran.

This research aimed to illustrate a data envelopment analysis (DEA) approach to assess EN Bank branch network performance. In this paper, we focus on deploying the DEA model to analyze bank branches' performance and which criteria can be selected as an input or output in developing the DEA model; of course, we concentrate on the suitable DEA models in Bank branch performance analysis. The main reason for using a DEA model instead of other summary ratios/indices is the difficulty of determining suitable weights for each efficiency component a priori. A DEA model shows a strong ability to choose weights objectively and generate a scalar-valued indicator. [12]

3.1. DEA Model

In this paper, according to Joseph C. Paradi et al. (2011), a two-stage Data Envelopment Analysis approach is developed to simultaneously benchmark operating units' performance along different dimensions (for line managers). A modified Slacks-Based Measure model (SBM) is applied for the first time to aggregate the obtained efficiency scores from stage one and generate a composite performance index for each unit. [8]

3.2. CCR vs. BCC model

In this study, the authors use both CCR and BCC, DEA models, and analyze all the abovementioned models in the CCR and BCC approach. In the CCR model, return to scale is constant, which means that by increasing or decreasing the inputs, outputs proportionally increase or decrease with a constant rate. Still, the rate of increase or decrease in outputs is not constant in the BCC model.

4. Results and Discussion:

For finding the suitable result to this question according to results of DEA models, it can be concluded that for reaching the efficiency line, each branch should decrease which inputs and how much and, of course, increase which outputs and how much, so practical program for each un efficient branch can be provided which define to increase which outputs and decrease which input and how much to increase or decrease. This result is presented in Table 1 just for inefficient branches. In this Table, both BCC and CCR model results are provided.

Table 1. Profitability Model

DMU	CCR E**	BCC E	CCR Reference set	BCC Reference set	Return to scale

					CC R
101 *	1.00***	1.00	101	101	DRS
102	1.00	1.00	102	102	DRS
103	1.00	1.00	103	103	DRS
104	0.87	0.87	115,116,133,142	115,116,117,141	DRS
105	0.94	0.98	108,142,147	108,111,120,142	IRS
106	1.00	1.00	106	106	IRS
107	0.95	0.96	101,116,117,142	101,116,117,137	IRS
108	1.00	1.00	108	108	DRS
109	0.63	0.70	101,116,117,142	101,117,120,133	IRS
110	1.00	1.00	110	110	DRS
111	1.00	1.00	111	111	DRS
112	0.65	0.77	111,114,123	108,111,149	IRS
114	1.00	1.00	114	114	DRS
115	1.00	1.00	115	115	DRS
116	1.00	1.00	116	116	DRS
117	1.00	1.00	117	117	DRS
118	0.96	0.98	116,133,140,142	116,133,137,138	IRS
119	0.92	0.92	116,133,140,142	116,133,137,140	IRS
120	1.00	1.00	120	120	IRS
121	0.74	1.00	103,106,108,110	121	IRS
122	0.86	0.92	126,127,140	127,138,150,152	IRS
123	1.00	1.00	123	123	DRS
124	1.00	1.00	124	124	IRS
125	0.89	0.99	116,142	116,131,137,142	IRS
126	1.00	1.00	126	126	DRS
127	1.00	1.00	127	127	DRS
128	0.98	1.00	126,127,140	128	IRS
129	1.00	1.00	129	129	IRS
130	1.00	1.00	130	130	DRS
131	1.00	1.00	131	131	IRS
132	0.96	0.97	127,134,140,150	127,134,138,140	IRS
133	1.00	1.00	133	133	IRS
134	1.00	1.00	134	134	DRS

135	1.00	1.00	135	135	IRS
136	0.91	0.93	116,120,123	114,120,123,149	IRS
137	1.00	1.00	137	137	IRS
138	0.94	1.00	126,127,131,140	138	IRS
140	1.00	1.00	140	140	DRS
141	1.00	1.00	141	141	IRS
142	1.00	1.00	142	142	DRS
143	0.88	0.88	123,127,131,140	123,127,131,140	DRS
145	0.92	1.00	116,140	145	IRS
146	0.89	0.92	123,126,127,140	123,126,127,138	IRS
147	1.00	1.00	147	147	DRS
148	1.00	1.00	148	148	IRS
149	1.00	1.00	149	149	IRS
150	1.00	1.00	150	150	IRS
151	0.83	0.90	101,110,116,123	101,116,123,131	IRS
152	1.00	1.00	152	152	DRS
153	0.81	0.83	115,127,133,140	127,137,140,141	IRS

* Each Branch Code **Efficiency *** 1 denote most efficient DMUs

According to the results of DEA models, it can be concluded that for reaching the efficiency line, each branch should decrease which inputs and how much and, of course, increase which outputs and how much, so practical program for each un efficient branch can be provided which define to increase which outputs and decrease which input and how much to increase or decrease.

Profitability and intermediary models are presented in Table 2. In this Table, it can be concluded that BCC models are more optimistic. The average efficiency score and the number of efficient branches in BCC models for both approaches are more than the CCR model. This indicated that branches are more homogeneous in the profitability approach than the intermediary model.

4.1. Super Efficiency Ranking

After defining the efficient and non-efficient branches in previous parts, the above results are aggregated to reach a final score for each branch and overall ranking of the studied branches.

As depicted before, the average efficiency of branches is high, the number of efficient branches is also high, and approximately 60% of studied branches are shown as efficient branches. In this model, the efficiency score can be variant from zero to infinity, but in ordinary models, the efficiency score can vary from zero to 1. Branches with more efficiency scores perform better in super-efficiency models than the others. The final results of super-efficiency analysis and the ranks within the branches are presented in Table 2.

Table 2 Super efficiency results

DMU	Profitability CCR Score	CCR Rank	BCC Score	BCC Rank	Intermediary CCR Score	CCR Rank	BCC Score	BCC Rank
101	1.91	6	2.57	6	1.29	21	1.47	14
102	1.02	31	1.00	27	14.67	3	1.00	25

103	1.65	9	3.87	4	2.18	9	3.62	8
104	0.87	44	0.87	47	0.70	38	0.73	48
105	0.94	37	0.98	37	1.04	27	1.05	23
106	1.05	25	1.07	21	1.71	14	2.95	11
107	0.95	35	0.96	40	0.85	32	0.85	40
108	1.56	11	5.26	3	1.65	15	6.43	5
109	0.63	50	0.70	50	0.67	42	0.74	46
110	1.98	4	25.62	1*	2.41	8	25.76	1*
111	1.36	14	1.92	8	1.04	28	1.08	21
112	0.65	49	0.77	49	0.67	41	0.78	45
114	1.36	15	3.82	5	1.27	22	1.93	12
115	1.02	30	1.03	25	0.78	35	0.82	43
116	1.31	16	5.89	2	1.40	19	13.42	3
117	1.10	23	1.11	18	1.22	23	1.32	16
118	0.96	33	0.98	38	0.44	48	0.83	41
119	0.92	39	0.92	43	0.57	44	0.57	50
120	1.06	24	1.09	20	1.17	24	1.20	17
121	0.74	48	1.16	16	1.95	11	3.00	10
122	0.86	45	0.92	42	21.49	2	22.40	2
123	1.63	10	1.00	27	1.41	18	1.00	25
124	1.14	20	1.22	13	0.86	31	1.06	22
125	0.89	42	0.99	36	0.68	40	0.91	38
126	1.93	5	1.00	27	28.42	1*	1.00	25
127	1.89	7	1.00	27	6.32	6	1.00	25
128	0.98	32	1.01	26	1.05	26	1.13	19
129	1.12	22	1.19	14	1.47	17	3.86	6
130	1.83	8	1.00	27	1.83	12	1.00	25

131	1.55	12	1.98	7	0.44	49	0.97	34
132	0.96	34	0.97	39	1.60	16	3.12	9
133	1.28	17	1.33	11	2.44	7	3.70	7
134	1.23	18	1.25	12	1.80	13	1.81	13
135	1.03	28	1.04	24	1.35	20	12.32	4
136	0.91	40	0.93	41	0.95	30	0.97	33
137	1.03	27	1.43	10	0.51	46	0.97	35
138	0.94	36	1.16	15	0.52	45	1.15	18
140	3.14	3	1.00	27	0.71	36	0.96	36
141	1.13	21	1.13	17	0.69	39	0.73	47
142	23.18	1*	1.00	27	9.68	5	1.00	25
143	0.88	43	0.88	46	0.70	37	0.82	42
145	0.92	38	1.05	22	0.37	50	1.02	24
146	0.89	41	0.92	44	0.82	33	0.93	37
147	6.54	2	1.00	27	2.12	10	1.00	25
148	1.22	19	1.54	9	0.81	34	0.88	39
149	1.02	29	1.10	19	1.04	29	1.43	15
150	1.04	26	1.05	23	1.06	25	1.12	20
151	0.83	46	0.90	45	0.65	43	0.80	44
152	1.47	13	1.00	27	13.95	4	1.00	25
153	0.81	47	0.83	48	0.48	47	0.67	49

* Highest Rank

4.2. Overall Results and Ranking

The authors defined the model for running the SBM model like Figure 2. In this model, each branch uses the profitability and intermediary efficiency scores as an output. A constant one is used as an input for each branch to have the same input for model consistency.

Table 3. Overall Scores and Ranking

The final results in Table 3 are compared with each branch's current EN bank score for validity purposes. Current EN bank scores are computed based on some internal indices of En bank. Also, in this Table, the type of each branch is defined. Excellent, grades 1, 2, and 3 are dedicated to each of them based on their capacity and performance in operation.

DMU	EN Bank Current Score	Branch Type	Efficiency Score	Rank
101	299372	Excellent	0.0987	14
102	445808	Excellent	0.5170	4
103	111441	1	0.1206	10
104	73072	1	0.0486	41
105	514094	Excellent	0.0620	33
106	71192	1	0.0876	17
107	41611	1	0.0559	36
108	182656	1	0.1005	13
109	62707	1	0.0408	48
110	188024	1	0.1381	8
111	253145	Excellent	0.0743	24
112	107248	1	0.0414	47
114	113815	1	0.0820	20
115	25862	2	0.0556	37
116	45762	1	0.0851	19
117	176155	1	0.0727	25
118	24325	2	0.0427	46
119	29599	2	0.0459	44
120	35474	2	0.0701	26
121	26566	2	0.0864	18
122	17286	2	0.7562	3
123	19668	2	0.0948	16
124	18566	2	0.0620	32
125	23179	2	0.0486	40
126	31087	2	1.0000	1**
127	41801	1	0.2652	7
128	14464	3	0.0636	30
129	25929	2	0.0816	21
130	147277	1	0.1145	12
131	10363	3	0.0668	27
132	16004	2	0.0811	22
133	21861	2	0.1183	11
134	37636	2	0.0960	15
135	53372	1	0.0751	23
136	35699	2	0.0584	34
137	7835	3	0.0473	42
138	10385	3	0.0449	45
140	17024	2	0.1353	9
141	23804	2	0.0560	35
142	63518	1	1.0000	1
143	23178	2	0.0490	39
145	7905	3	0.0396	49
146	24021	2	0.0534	38
147	681327	Excellent	0.2822	6
148	18533	2	0.0625	31
149	12347	3	0.0643	29
150	20032	2	0.0658	28
151	20444	2	0.0459	43

152	38091	2	0.5062	5
153	16963	2	0.0395	50

** First rank

According to Table 3, the reader can compare the current EN bank score for each branch by its DEA overall score, and of course, their rank based on these scores can be supplied. Comparing them can lead the reader to find the compatibility of the current system by DEA ranking of branches.

5. Conclusion

According to the gained results, branch efficiency can be determined by Table 1, columns 2 and 3, and Table 6. The most efficient branches can be determined in Table 2, columns 3, 5, 7, and 9.

It should be clarified that because a bank branch has a lot of processes and services and several inputs and outputs, lateral research mostly developed a multi-approach analysis to branch performance analysis.

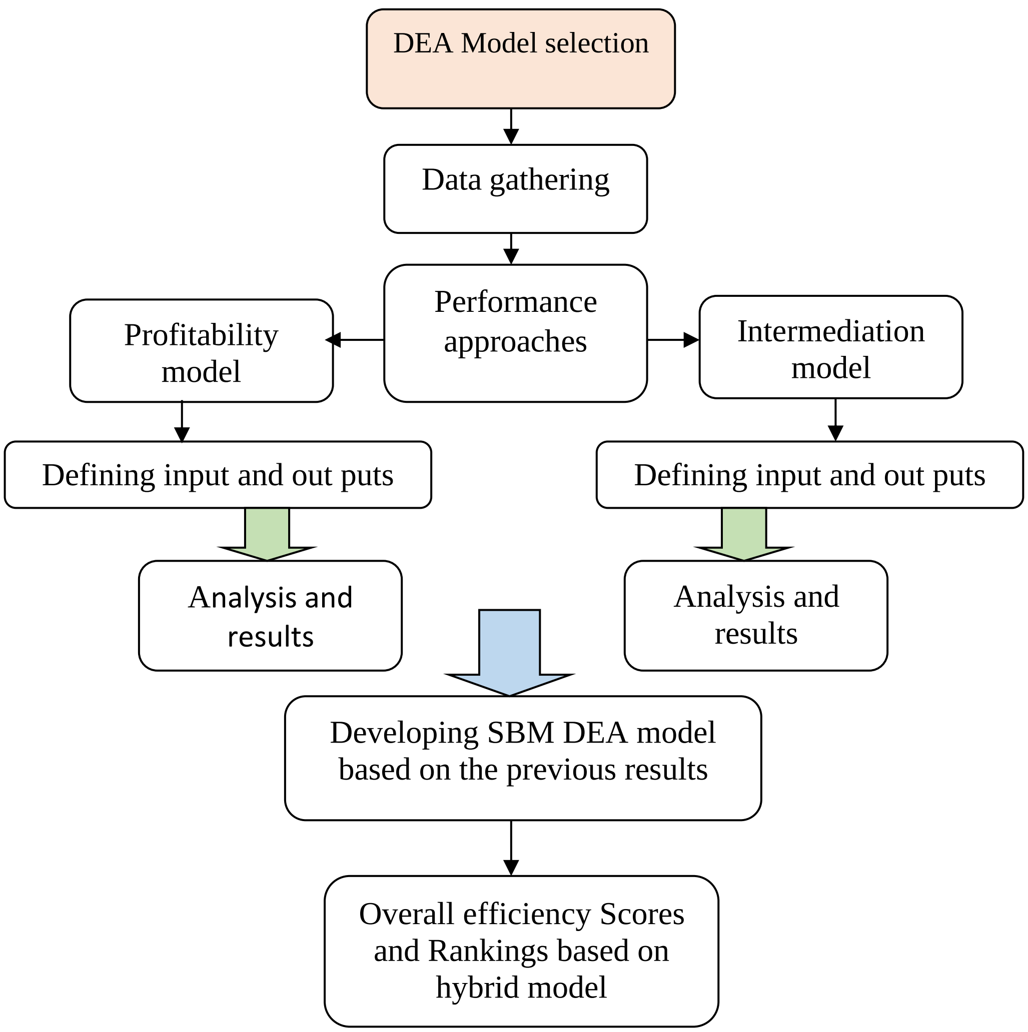

Figure 1. Model Selection

The authors use CCR, BCC, and DEA models (Figure 1). And analyze all models mentioned above in CCR and BCC approach together. In the CCR model, return to scale is constant, which means that by increasing or decreasing the inputs, outputs proportionally increase or decrease with a constant rate. Still, in the BCC model, the rate of increase or decrease in outputs is not constant, which means that variation in outputs may be more or less in respect to variation in inputs.

In summary, both profitability and intermediary models are presented in Table 4. In this Table, it can be concluded that BCC models are more optimistic. The average efficiency score and the number of efficient branches in BCC models for both approaches are more than the CCR model.

Table 4. Comparison of Profitability versus Intermediary Model Results

	Profitability		Intermediary	
	CCR Model	BCC Model	CCR Model	BCC Model
No. DMUs	50	50	50	50
Efficient DMUs	31	35	29	32
E Average	0.950	0.970	0.857	0.938
E SD	0.086	0.062	0.194	0.105
E Min	0.634	0.701	0.372	0.571

After defining the efficient and non-efficient branches, the gain results are aggregated to reaching a final score for each branch and overall ranking of the studied branches.

Table 5. Super Efficiency Results

	Profitability				Intermediary			
DMU	CCR Score	CCR Rank	BCC Score	BCC Rank	CCR Score	CCR Rank	BCC Score	BCC Rank
101	1.91	6	2.57	6	1.29	21	1.47	14
102	1.02	31	1.00	27	14.67	3	1.00	25
103	1.65	9	3.87	4	2.18	9	3.62	8
104	0.87	44	0.87	47	0.70	38	0.73	48
105	0.94	37	0.98	37	1.04	27	1.05	23
106	1.05	25	1.07	21	1.71	14	2.95	11
107	0.95	35	0.96	40	0.85	32	0.85	40
108	1.56	11	5.26	3	1.65	15	6.43	5
109	0.63	50	0.70	50	0.67	42	0.74	46
110	1.98	4	25.62	1*	2.41	8	25.76	1*

111	1.36	14	1.92	8	1.04	28	1.08	21
112	0.65	49	0.77	49	0.67	41	0.78	45
114	1.36	15	3.82	5	1.27	22	1.93	12
115	1.02	30	1.03	25	0.78	35	0.82	43
116	1.31	16	5.89	2	1.40	19	13.42	3
117	1.10	23	1.11	18	1.22	23	1.32	16
118	0.96	33	0.98	38	0.44	48	0.83	41
119	0.92	39	0.92	43	0.57	44	0.57	50
120	1.06	24	1.09	20	1.17	24	1.20	17
121	0.74	48	1.16	16	1.95	11	3.00	10
122	0.86	45	0.92	42	21.49	2	22.40	2
123	1.63	10	1.00	27	1.41	18	1.00	25
124	1.14	20	1.22	13	0.86	31	1.06	22
125	0.89	42	0.99	36	0.68	40	0.91	38
126	1.93	5	1.00	27	28.42	1*	1.00	25
127	1.89	7	1.00	27	6.32	6	1.00	25
128	0.98	32	1.01	26	1.05	26	1.13	19
129	1.12	22	1.19	14	1.47	17	3.86	6
130	1.83	8	1.00	27	1.83	12	1.00	25
131	1.55	12	1.98	7	0.44	49	0.97	34
132	0.96	34	0.97	39	1.60	16	3.12	9
133	1.28	17	1.33	11	2.44	7	3.70	7
134	1.23	18	1.25	12	1.80	13	1.81	13
135	1.03	28	1.04	24	1.35	20	12.32	4
136	0.91	40	0.93	41	0.95	30	0.97	33
137	1.03	27	1.43	10	0.51	46	0.97	35
138	0.94	36	1.16	15	0.52	45	1.15	18

140	3.14	3	1.00	27	0.71	36	0.96	36
141	1.13	21	1.13	17	0.69	39	0.73	47
142	23.18	1*	1.00	27	9.68	5	1.00	25
143	0.88	43	0.88	46	0.70	37	0.82	42
145	0.92	38	1.05	22	0.37	50	1.02	24
146	0.89	41	0.92	44	0.82	33	0.93	37
147	6.54	2	1.00	27	2.12	10	1.00	25
148	1.22	19	1.54	9	0.81	34	0.88	39
149	1.02	29	1.10	19	1.04	29	1.43	15
150	1.04	26	1.05	23	1.06	25	1.12	20
151	0.83	46	0.90	45	0.65	43	0.80	44
152	1.47	13	1.00	27	13.95	4	1.00	25
153	0.81	47	0.83	48	0.48	47	0.67	49

* Highest Rank

The highest rank in all models based on their return to scale is presented in Table 5. These variant results based on different models make the reader a little bewildered. To overcome this, a combining model is needed to aggregate all the results in a valid single rank, so the SBM model can be useful here, which the discussion of the next section is.

Table 6. Intermediary Model

DMU	CCR E	BCC E	CCR Reference set	BCC Reference set	Return to scale CCR
101	1	1	101	101	CRS
102	1	1	102	102	CRS
103	1	1	103	103	CRS
104	0.7	0.73 17	116,126,142,147	108,126,142,147,150	IRS
105	1	1	105	105	CRS
106	1	1	106	106	CRS
107	0.853	0.85	106,126,142,147	106,121,126,142,147	IRS
108	1	1	108	108	CRS
109	0.67	0.74	102,121,126,129, 134	102,121,134,149,	IRS
110	1	1	110	110	CRS
111	1	1	111	111	CRS
112	0.67	0.78	126,147	102,111,117,133,147	IRS

114	1	1	114	114	CRS
115	0.783	0.81	106,126,133,134	121,126,133,134,149	IRS
116	1	1	116	116	CRS
117	1	1	117	117	CRS
118	0.447	0.83	116,126,142,147	121,133,138,142	IRS
119	0.572	0.51	116,120,134,142, 149	116,120,126,134,142	DRS
120	1	1	120	120	CRS
121	1	1	121	121	CRS
122	1	1	122	122	CRS
123	1	1	123	123	CRS
124	0.864	1	103,110,116,123, 142,152	124	IRS
125	0.68	0.90	103,116,126,134, 142	103,126,142,149,152	IRS
126	1	1	126	126	CRS
127	1	1	127	127	CRS
128	1	1	128	128	CRS
129	1	1	129	129	CRS
130	1	1	130	130	CRS
131	0.433	0.97	126,130,134	134,138,149	IRS
132	1	1	132	132	CRS
133	1	1	133	133	CRS
134	1	1	134	134	CRS
135	1	1	135	135	CRS
136	0.95	0.97	120,126,135,149	108,120,126,135	IRS
137	0.513	0.97	121,126	121,126,149	IRS
138	0.52	1	123,126,134,149	138	IRS
140	0.71	0.96	123,126,134,149, 152	134,138,149,152	IRS
141	0.69	0.73	121,126,134	121,134,149	IRS
142	1	1	142	142	CRS
143	0.69	0.81	126,134,149	126,134,149	IRS
145	0.37	1	108,116,120,126, 149	145	IRS
146	0.82	0.93	126,130,134,150,	126,134,149	IRS
147	1	1	147	147	CRS
148	0.81	0.88	121,134	121,134,149	IRS
149	1	1	149	149	CRS
150	1	1	150	150	CRS
151	0.65	0.80	102,127,134,149	102,127,134,149	IRS
152	1	1	152	152	CRS
153	0.47	0.67	102,121,126,127	121,127,149	IRS

It is clear that in CCR or BCC model, we can have efficient DMUs while they are not Pareto efficient, which means they could have more than needed inputs or less than needed outputs. For running the SBM model here, the authors defined a model; in this model, the efficiency scores of the profitability and intermediary are used as an output for each branch, and a constant one is used as an input for each branch to have the same input model consistency reason.

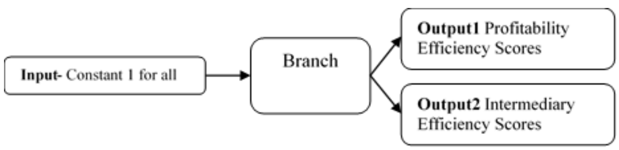

Figure 2. SBM Model Structure

Finally, according to Table 3, the reader can compare the current EN bank score for each branch by its DEA overall score, and of course, their rank based on these scores can be supplied. Comparing them can lead the reader to find the compatibility of the current system by DEA ranking of branches.

REFERENCE

1. A.Udhayakumar, V.Charles, Mukesh Kumar, Stochastic simulation-based genetic algorithm for chance-constrained data envelopment analysis problems. Omega 39(2011)387–397.
2. A.S. Camanho, R.G. Dyson, Cost efficiency measurement with price uncertainty: a DEA application to bank branch assessments. European Journal of Operational Research 161 (2005) 432–446.
3. Alirezaee, M., Howland, M., & van de Panne, C. (1998). Sampling size and efficiency bias in data envelopment analysis. Journal of Applied Mathematics and Decision Sciences, 2, 51–64.
4. Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. Management Science, 30(9), 1078–1092.
5. Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision-making units. European Journal of Operational Research, 2(6), 429–444.
6. Charnes, A., Cooper, W.W., Golany, B., Seiford, L.M., Stutz, J., 1985b.Foundations of data envelopment analysis and Pareto–Koopmans empirical production functions. Journal of Econometrics 30, 91–107.
7. Elyasiani, E., & Mehdian, S. (1995). The comparative efficiency performance of small and large U.S. commercial banks in the pre-and 53 post-deregulation eras.Applied Economics, 27(11), 1069–1079.
8. Joseph C. Paradi, Stephen Rouatt, HaiyanZhu, Two-stage evaluation of bank branch efficiency using data envelopment analysis.Omega 39(2011)99–109.
9. Mohamed M. Mostafa, Modeling the efficiency of top Arab banks: A DEA–neural network approach. Expert Systems with Applications 36 (2009) 309–320.
10. Necmi K. Avkiran, Association of DEA super-efficiency, estimates with financial ratios: Investigating the case for Chinese banks. Omega 39(2011)323–334.
11. Siems, T. F. (1992). Quantifying management's role in bank survival. Federal Reserve Bank of Dallas Economic Review (January), 29–41.
12. Tyrone T. Lin, Chia-Chi Lee, Tsui-Fen Chiu, Application of DEA in analyzing a bank's operating performance. Expert Systems with Applications 36 (2009) 8883–8891.
13. Yao Chen, Wade D. Cook, Joe Zhu. Deriving the DEA frontier for two-stage processes. European Journal of Operational Research 202 (2010) 138–142.
14. Meryem Duygun Fethi, Fotios Pasiouras, Assessing bank efficiency and performance with operational research and artificial intelligence techniques: A survey. European

Journal of Operational Research 204 (2010) 189–198.
15. William W.Cooper, Lawrence M.Seiford, Kaoru Tone (1999). Data Envelopment Analysis
16. Zaki, A. E., Rizk, M. F., Sakoury, M. M., Ababtain, H. A. S., AL-Sabti, N., & Aldossary, L. Y. K. (2020). Analyzing the role of big data in activating social responsibility, supporting the sustainable development of Saudi banks. Journal of Advanced Pharmacy Education and Research, 10(1), 207-213
17. Makhdoom, T. R., Shaikh, M. A., & Baloch, M. N. (2021). Traditional Leadership Styles Influencing Employee Work Behaviors In Islamic Banks Of Sindh, Pakistan. Journal Of Organizational Behavior Research, 6(1), 46-58