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Application of Sensitivity Analysis and Super-Efficiency DEA Models on Efficiency Evaluation of Public Sector Banks in India

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Abstract

The assessment of performance or efficiency is an essential step in the production process. Performance and efficiency evaluations can be done using parametric or non-parametric approaches. When analysing the effectiveness of similar organisations, also known as Decision Making Units (DMUs), with many inputs and outputs, one of the most widely used non-parametric methodology is Data Envelopment Analysis (DEA), which is based on a linear programming approach. Inefficient units are benchmarked (peers) and efficiency scores are provided by DEA for each DMU. Based on the number of peers, the Decision Making Units might then be ranked. A Tie between ranks, however, can happen. Andersen-Peterson's (1993) model aids in breaking the tie. The super-efficiency model produces an infeasible result, which is confirmed by applying the prerequisites for infeasibility identification put forth by Seiford & Zhu (1999). In this paper, we present the results of our empirical investigation of Public Sector Banks in India during the 2019–20 period, focussing on three inputs and two outputs. We used variable return to scale (VRS) assumption based Banker Charnes and Cooper (BCC) and super-efficiency models, and also identified the infeasibility problem and performed sensitivity analysis. Finally, a stability region was constructed.

Keywords: Data Envelopment Analysis, Decision Making Units, Super-Efficiency, Infeasibility, Sensitivity Analysis, Stability Region

JEL Classification: B23, C01, C02, C61, C44, G21, L25

Introduction

A crucial component of the entire financial system is banking. By offering infrastructure, financing, and investment, it influences the national economy. Global economies are supported by the banking sector. Any nation's economic development and progress are greatly influenced by the banking industry. India's economy is among the fastest-growing in the world, and the country's banking industry has been vital to this expansion. Recent technological advancements, a rise in foreign investment, and regulatory changes have all had a substantial impact on the Indian banking industry.

After a long and arduous history, the Indian banking industry has become a vital component of the country's economy. The industry has undergone a significant transformation in recent years with the adoption of new technologies, the introduction of cutting-edge goods and services, and the extension of its reach to previously marginalised groups in society. Notwithstanding the various challenges the industry faces, it is well-positioned to overcome them and continue expanding. Future economic growth and prosperity in India are expected to be significantly influenced by the banking sector. There are many different kinds of banks in this industry, such as foreign, cooperative, private, and public-sector banks.

A public-sector bank is one that the government either owns outright or has a significant stake (greater than 51%) in the bank. The author of this paper is interested in using Data Envelopment Analysis to evaluate the performance of Public Sector Banks in India. A non-parametric method

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for comparing the relative effectiveness of comparable organisations – often referred to as Decision Making Units (DMUs), – is Data Envelopment Analysis. This mathematical programming method, which is based on a linear programming problem, is an effective instrument for gauging the effectiveness of decision-making units. Every decision-making unit uses identical inputs and generates identical outputs. DEA estimates the efficiency frontier by analysing the DMUs with multiple inputs and multiple outputs. The efficiency may be technical, scale, allocative, and economical, etc. In recent years, DEA has been applied by many researchers for solving the different types of real-life problems. The real-life applications of DEA include various fields such as industries, banking sectors, health care institutions, educational and agricultural sector, etc. Thus, DEA has found its applications in the service and non-service sectors.

The data considered for analysis are taken from reports relating to Performance Highlights of Public Sector Banks 2019–20, published by the Department of Research and Statistics, Indian Banks' Association, Mumbai. In 2020, four significant public sector banks in India were formed with the merger of more than ten banks. But in 2019, there were 18 Public Sector Banks in India, and all of them are considered for the performance analysis with reference to the study period 2019-20. Each bank is considered as a decision-making Units. Here the author considers 5 input and 3 output variables and all these variables are judiciously selected based on prior studies relating to banking performance.

Review of Literature

As of 1978, Data Envelopment Analysis has emerged as a new management science for the performance analysis of production units and a very potent tool to measure the technical efficiency of the decision making units, despite the fact that there are many other techniques available for measuring productivity efficiency. Data Envelopment Analysis is an extension of Operations Research, which is based on optimisation strategies for resource allocation problems. Since 1957, a significant number of books and over 7,000 research articles have been produced in the field of Data Envelopment Analysis.

"The vector of inputs is technically efficient if and only if increasing any output or reducing any input is achievable only by increasing some other input or decreasing some other output" – the definition of technical efficiency of input based on disposability criterion (Koopman, 1951). A measure of technical efficiency in terms of maximum possible proportionate reduction of all variable inputs or maximum possible proportionate expansion of all output is called radial measure (Debreu, 1951).

A groundbreaking contribution to the field of productive efficiency measurement has been made. It changed the course of development to focus on the different kinds of efficiencies known as "scale", "allocative", and "technical" (Farrel, 1957). Therefore, the foundation for the study of frontier analysis was established by the series of technological efficiency (Debreu, 1951; Farrel, 1957).

The first comprehensive investigation of DEA was done and a mathematically based linear fractional programming scheme was created (Charnes & Cooper, 1962). An effective linear programming-based computing procedure based on Farrel's theories for a range of Technical Efficiency problems in the situation of numerous outputs was developed (Bressler, 1966; Boles, 1966; Seitz, 1966; Sitorus, 1966).

The classic DEA model, which is an extension of the production efficiency measure first introduced by Farrel in 1957, was developed (Charnes, Cooper & Rhodes, 1978). It is based on the Constant Returns to Scale assumption (CRS) and is known as the CCR Model. Under the restrictions that the similar ratio must be less than or equal to unity for all DMUs, the suggested model (CCR Model) gives an efficiency measure of every decision making unit in the sample that maximises the ratio of weighted outputs to weighted inputs.

The CCR Model was extended (Banker, Charnes & Cooper, 1984), and it allows for the Variable Returns to Scale assumption (VRS). It is now possible to ascertain whether operations are carried out in regions of growing, constant, or declining returns to scale in this model thanks to the addition of a new independent variable by Banker et al. For each of the sample's decision-making units, this model offers estimates of its technical and scale efficiency in relation to the efficiency frontier.

A system for evaluating efficient units and facilitating comparison based on the parametric method in Data Envelopment Analysis was created (Anderson &

Peterson, 1993). The application of super-efficiency to DEA sensitivity analysis was proposed (Zhu, 2001). This work also develops the necessary and sufficient conditions to keep the same efficiency categorisation when data variation is done for all DMUs.

The problem of infeasibility that occurs in super-efficiency DEA models was addressed (Seiford & Zhu, 1999). This study also suggests the necessary and sufficient conditions for the super-efficiency DEA Model to be infeasible. The infeasibility that happened in the super-efficiency DEA Models led the authors to conclude that not all efficient decision making units could be ranked in order.

Data Envelopment Analysis was used in the banking industry (Sherman & Gold, 1985) and assessed the operational effectiveness of 14 savings bank branches. Data Envelopment Analysis was also used to examine the banking industry's performance in the United States and a few European nations (Pastor, Perez & Quesada, 1997). An intermediation approach was employed to study the efficiency of 750 chosen European banks (Casu & Molyneux, 2003). An interval DEA technique was used to measure the efficiency of the Turkish banking industry (Budak & Erpolat, 2013) and came to the conclusion that interval DEA methods produce more selective results than DEA.

Under the VRS assumption, efficiency estimates for the cost, revenue, and profit of Indian public sector banks in the years 2015–2016 were assessed (Jayarani & Prakash, 2017). The study's empirical analysis reveals that a bigger proportion of DMUs exhibit profit efficiency, with average cost efficiency standing 51 points higher than average revenue efficiency and average profit efficiency.

Yet another study examines technical efficiency and its correlates in respect of the banking industry in India during 1995–2016 using Data Envelopment Analysis (Khurana & Khosla, 2019). The technical efficiency of 94 public, private, foreign, and small financial commercial banks in India in 2019 using the data envelopment analysis (DEA) was measured, and the determinants of technical efficiency were analysed by applying the Tobit regression method (Lakshmanasamy, 2021). Attempts have also been made to examine the productive efficiency of commercial banks in India, by using the Data Envelopment Analysis (DEA) technique for a sample of 70 commercial banks.

Methodology

Banker Charnes and Cooper (BCC) Model

Banker, Charnes, and Cooper (1984) proposed a model with a convexity constraint which permits variable return to scale (VRS) assumptions. This model is generally known as input oriented BCC DEA Model and is presented below.

Assume that there are n units, each consuming m inputs to produce s outputs. Let y_{rj} denote the level of the rth output (r = 1,2,…,s) from unit j (j = 1,2,…,n) and x_{ij} denotes the level of the ith input (i = 1,2,…,m) to the jth unit.

Model I : BCC Input Oriented DEA Model

$$\theta^* = \min \theta$$

Subject to

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{io} \; for \; i = 1,2, \dots m$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro} \; for \; r = 1,2, \dots s$$

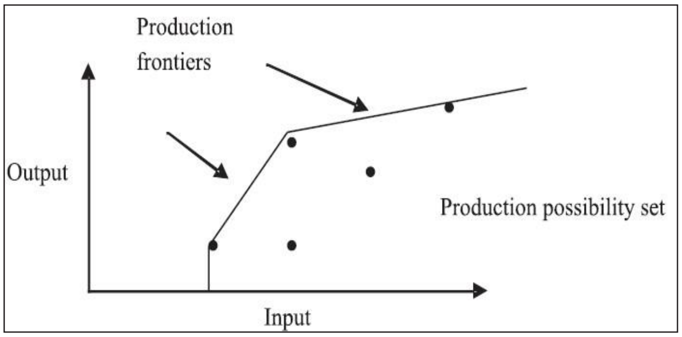
$$\sum_{j=1}^{n} \lambda_j = 1$$

$$\lambda_j \geq 0 \; for \; j = 1,2, \dots n$$

This model is termed as envelopment version and it obtains efficiency score (θ^*) and weights (λ) for each DMU. The variable θ, which appears in the objective function, represent the amount of proportional reduction applied to all inputs of the evaluated DMU to improve its efficiency. It may be noted that the simultaneous reduction of all inputs results in a radial movement towards the envelopment surface. The evaluated DMU (DMU_o) is said to be efficient if:

- $\theta^* = 1, \lambda_j = 1 \; for \; j = o \; and \; \lambda_j = 0 \; for \; j \neq o$
- All slacks are zero.

If $0 < \theta^* < 1$, it indicates inefficiency. BCC Model is similar to the CCR Model except for the convexity constraint $\sum_{j=1}^{n} \lambda_j = 1$. This convexity constraint ensures the piecewise linear approximation to the efficiency frontier and concave characteristics which leads to VRS characterisation. These aspects are pictorially represented as follows:



Production Frontier of the BCC Model

The above model is a primal one and its dual known as BCC output maximisation is given below:

Model II: BCC Output Maximisation Model

Here, Banker et al. (1984) introduced a new separate variable in the objective function which admits VRS characterisation. This variable identifies whether the operations were conducted in the region of increasing, constant or decreasing return to scale in case of multiple input and multiple output scenario.

$$\max_{u,v} Z_o(u,v) = \sum_{r=1}^{s} u_r y_{ro} + u_0$$

Subject to

$$\sum_{i=1}^{m} v_i x_{io} = 1$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + u_0 \leq 0 \; for \; j = 1,2, \dots n$$

$$v_i \geq \varepsilon \; for \; i = 1,2, \dots m$$

$$u_r \geq \varepsilon \; for \; r = 1,2, \dots s$$

$$u_0 \;\; free \; in \; sign$$

The optimal solution of this model (Z_o^*, u_r and v_i) represents the efficiency scores, weights of outputs and inputs respectively for the evaluated DMU$_o$. DMU$_o$ is efficient if and only if Z_o^*= max Z_o= 1, otherwise it is inefficient. Next, BCC developed output oriented DEA Model (envelopment version) and the same is given below:

Model III: BCC Output Oriented DEA Model

$$\phi^* = \max \phi$$

Subject to

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{io} \; for \; i = 1,2, \dots m$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq \phi y_{ro} \; for \; r = 1,2, \dots s$$

$$\sum_{j=1}^{n} \lambda_j = 1$$

$$\lambda_j \geq 0 \; for \; j = 1,2, \dots n$$

This model results in efficiency score (ϕ^*) and weights (λ) for each DMU. The above model maximises on ϕ to achieve proportional output augmentation with ϕ = 1 indicating efficiency and ϕ> 1 indicating an extent of radial inefficiency related to the best practice DMU included in the sample.

Super-Efficiency Models

It is well established that the fundamental DEA methodology—CCR and BCC—is an extremely effective instrument for evaluating the effectiveness or performance of comparable organisations. However, DEA displays many units as efficient in the situation of a high number of inputs and outputs because of the restriction on the efficiency score that ϕ^*= 1 in output oriented. As a result, there may be ties in rankings among the DMUs in the sample taken into consideration for the study when we attempt to rate the DMUs based on the peer summary.

The idea of super-efficiency was presented in order to tackle this problem. Conventional DEA models assess a DMU's effectiveness or performance in comparison to other DMUs in the set that includes the DMU under evaluation. On the other hand, the resultant DEA models are referred to as super-efficiency DEA Models when the DMU being evaluated is not part of the envelopment model's reference set.

VRS Super-Efficiency DEA Models

Seiford and Zhu (2002) proposed VRS SE DEA model based on Anderson and Peterson (1993) SE DEA model in respect of input oriented and output oriented and are presented below:

Model IV: VRS SE DEA Model (Input Oriented)

$\min \theta^{SE}$

Subject to

$$\sum_{\substack{j=1 \\ j\neq o}}^{n} \lambda_j x_{ij} \leq \theta^{SE} x_{io} \; for \; i = 1,2, \dots m$$

$$\sum_{\substack{j=1 \\ j\neq o}}^{n} \lambda_j y_{rj} \geq y_{ro} \; for \; r = 1,2, \dots s$$

$$\sum_{\substack{j=1 \\ j\neq o}}^{n} \lambda_j = 1$$

$$\lambda_j \geq 0 \; for \; j \neq o$$

This model yields SE Scores of the evaluated DMU and weights to all other DMUs included in the set. The SE Scores categorise (Charnes, Cooper & Thrall, 1991) the set of DMUs into four groups, namely.

- *E*: set of extreme efficient DMUs ($\theta^{SE^*} > 1$)
- *E′*: set of efficient DMUs that are not extreme points ($\theta^{SE^*} = 1$)
- *F*: set of weakly efficient DMUs ($\theta^{SE^*} = 1$ but with non-zero slacks)
- *N*: set of inefficient DMU ($\theta^{SE^*} < 1$)

The new facet could be formed by the reference set (which may include *F* and *N*) corresponding to each extreme efficient DMU in the set *E*. This new facet represents the minimum input combination used to produce the same level of output.

Model V: VRS SE DEA Model (Output Oriented)

$\max \phi^{SE}$

Subject to

$$\sum_{\substack{j=1 \\ j\neq o}}^{n} \lambda_j x_{ij} \leq x_{io} \; for \; i = 1,2, \dots m$$

$$\sum_{\substack{j=1 \\ j\neq o}}^{n} \lambda_j y_{rj} \geq \phi^{SE} y_{ro} \; for \; r = 1,2, \dots s$$

$$\sum_{\substack{j=1 \\ j\neq o}}^{n} \lambda_j = 1$$

$$\lambda_j \geq 0 \; for \; j \neq o$$

The solution of the model yields SE Scores of the evaluated DMU and weights to all other DMUs in the sample. The SE Scores categorise (Charnes, Cooper & Thrall, 1991) the set of DMUs into four groups, namely.

- *E*: set of extreme efficient DMUs ($\theta^{SE^*} > 1$)
- *E′*: set of efficient DMUs that are not extreme points ($\theta^{SE^*} = 1$)
- *F*: set of weakly efficient DMUs ($\theta^{SE^*} = 1$ but with non-zero slacks)
- *N*: set of inefficient DMU ($\theta^{SE^*} < 1$)

The new facet formed by the reference set represents that no other DMU produces the maximum output with the given input combinations. It may be noted that the frontier line will not alter if the inefficient and weak efficient DMUs are excluded from the new facet.

Problem of Infeasibility

It is known that the evaluated DMU is excluded from the reference set in the SE DEA Models and it causes the problem of infeasibility. A necessary and sufficient condition says that infeasibility occurs in the case of extreme efficient DMUs. Also, it may be noted that extreme efficient DMUs have either feasible or infeasible solution. Infeasibility may arise in CRS SE input oriented DEA Model with the necessary and sufficient condition in case of occurrence of certain patterns of zero data in inputs and outputs (Zhu, 1996). But the CRS SE output oriented DEA Model does not encounter the problem of infeasibility. The problem of infeasibility mainly arises in VRS SE DEA Model, because of its scale assumption (VRS). Chen and Liang (2011) stated the following theorem which explains the sufficient condition for infeasibility in VRS SE DEA Model.

Theorem 1: Statement

A sufficient but not necessary condition for the infeasibility of the input-oriented VRS SE models is that there exists at least one output that has a value for the evaluated DMU_o greater than the values of any other DMUs.

Theorem 2: Statement

A sufficient but not necessary condition for infeasibility of the output-oriented VRS SE models is that there exists at least one input that has a value for the evaluated DMU_o greater than the values of any other DMUs.

It may be noted that efficient DMU under the standard BCC DEA model is either extreme efficient or infeasible in the VRS SE Model. Lee, Chu, and Zhu (2011) proposed the following theorems for the identification of infeasibility that arises in input oriented, and output oriented models

Theorem 3: Statement

The input-oriented super-efficiency VRS model is infeasible if and only if where is the optimal value to

$$g^* = \max g$$

Subject to

$$\sum_{\substack{j=1\\ j\neq o}}^{n} \lambda_j y_{rj} \geq g y_{ro} \; for\; r = 1,2,\dots s$$

$$\sum_{\substack{j=1\\ j\neq o}}^{n} \lambda_j = 1$$

$$\lambda_j \geq 0 \; for\; j \neq o$$

Theorem 4: Statement

The output-oriented super-efficiency VRS model is infeasible if and only if where is the optimal value to

$$h^* = \min h$$

Subject to

$$\sum_{\substack{j=1\\ j\neq o}}^{n} \lambda_j x_{ij} \leq h x_{io} \; for\; i = 1,2,\dots m$$

$$\sum_{\substack{j=1\\ j\neq o}}^{n} \lambda_j = 1$$

$$\lambda_j \geq 0 \; for\; j \neq o$$

Efficiency Sensitivity Analysis

Sensitivity analysis plays a vital role in the performance evaluation through Data Envelopment Analysis. In recent years, many researchers have studied efficiency sensitivity to perturbations in the data which is an important issue in DEA. Initially Charnes, Cooper, Golany, Seiford and Stutz (1985) studied sensitivity analysis that examines the change in single output. Further, Ahn and Seiford (1993) focussed on sensitivity of DEA results to the variable and model selection. Besides, some studies on sensitivity analysis were developed for the determination of range within which the variation is possible for any DMU. The degree of freedom approach, algorithmic approach, metric approach and multiplier model approach are some more avenues for studying sensitivity analysis in DEA. It may be noted that super-efficiency DEA is another approach for studying DEA Sensitivity Analysis and it allows perturbations in data to preserve efficiency classification in the following cases:

- either in any input or any output in test DMU.
- either in any input or any output in test DMU and remaining DMUs.
- any specific inputs and outputs in test DMU and remaining DMUs.

In this study, the author attempted DEA sensitivity analysis based on SE DEA model (Zhu, 1996), in the case of data perturbations to output only in test DMU.

It is obvious that by increasing any output or decreasing any input in the test DMU, the application of sensitivity analysis to perturbations in the data does not worsen the efficiency classification. So sensitivity analysis may be suggested to perform in the situation where decreasing any output or increasing any input alter the efficiency classification. Below are the forms, which may be considered for proportional increase of inputs or proportional decrease of outputs.

$$\hat{x}_{io} = \beta_i x_{io}; \qquad \beta_i \geq 1, i = 1,2, \dots m \tag{3.1}$$

$$\hat{y}_{ro} = \alpha_r y_{ro}; \qquad 0 < \alpha_r \leq 1, r = 1,2, \dots s \tag{3.2}$$

where x_{io} and are the inputs and outputs of the specific extreme efficient DMU_o respectively. Zhu (2003) stated that any increase of input or decrease of output will definitely change the status of DMUs in the efficient set E′ to the inefficient set N. The DMUs in the weak efficient set retain their same status irrespective of the amount of inputs increased or the amount of output decreased. So the sensitivity issues in the set E or F can be ignored. Thus, only the set of extreme efficient DMUs (E) would be subjected for sensitivity analysis. In this context stability region could be constructed for every extremely efficient DMU to maintain its efficiency status.

kth Specific DEA Models

Seiford and Zhu (1998) suggested VRS kth specific DEA models in both orientations to construct the stability region for the extremely efficient DMUs, and the same is listed below:

Model VI: VRS kth Specific Output Oriented DEA Model

$$\max \alpha_k^o \ \ for\ each\ k = 1,2, \dots s$$

Subject to

$$\sum_{\substack{j=1 \\ j\neq o}}^{n} \lambda_j y_{rj} \geq \alpha_k^o y_{ro}$$

$$\sum_{\substack{j=1 \\ j\neq o}}^{n} \lambda_j y_{rj} \geq y_{ro}\ for\ r \neq k$$

$$\sum_{\substack{j=1 \\ j\neq o}}^{n} \lambda_j x_{ij} \leq x_{io}\ for\ i = 1,2, \dots m$$

$$\sum_{\substack{j=1 \\ j\neq o}}^{n} \lambda_j = 1$$

$$\lambda_j \geq 0\ for\ j \neq o$$

For the above model, $x_{ij}((i = 1,2,\dots m)$ and $y_{rj}(r = 1,2,\dots s)$ represent the i^{th} input and r^{th} output of DMU_j $(j = 1,2,\dots n)$ respectively. Here the optimal $(\alpha^*_k,\ k = 1,2,\dots s)$ values of the model provide hypothetical frontier points. This frontier points from the output stability region that allows a possible output decrease in each individual output for the observed DMU_o. Thus DMU_o could preserve its status in the same efficiency classification keeping all other outputs constant. Zhu (2003) defines the following output stability region:

Definition

A region of allowable output decrease is called an Output Stability Region (OSR) if and only if DMU_o remains efficient after such decreases occur.

By solving the above models for each extremely efficient DMU, the solution obtained may be feasible or infeasible. The output stability region is of the form $\alpha_k^o < \alpha_k \leq 1$ in case of feasibility and it allows maximum α_k^o times of decrease in specific k^{th} output from current level to preserve same efficiency classification. $\alpha_k^o < \alpha_k \leq 1$, the adjusted factor, is an arbitrary value and it lies within the output stability region ($\alpha_k^o < \alpha_k \leq 1$). In the case of infeasibility, the output stability region is of the form $\alpha_k \leq 1$. The same efficiency classification can also be preserved by any value lesser than or equal to one multiplied with the specific output. Thus, the OSR is of the closed form in case of feasibility and has no lower limit in case of infeasibility for data variation.

Zhu (2005) explains infeasibility and stability for the kth specific model through the following theorems:

Theorem 5: Statement

For an efficient DMU_o, a decrease of the output only, Model VI is infeasible, if and only if the amount of output of DMU_o can be decreased without limitation while maintaining the efficiency of DMU_o.

The above discussions clearly explain the application of the data variation to the test DMU for a specific output.

Data Structure

To assess the performance of both Public Sector Banks functioning in India, BCC output oriented DEA Models are applied to measure the technical efficiency in this study. The author has selected input and output variables for this study after careful examination of various past studies relating to the performance in National and International Banking Sectors. Further, the author claims that the selection of variables including input and output in this study is extremely important for the production process. Besides, attempts are made for testing the data consistency and data validity.

The Public Sector Banks (DMUs) considered for this study are listed in the following Table 1.

Table 1: List of Public Sector Banks

Sr. No.	*Name of the Bank*	*DMU*
1.	Allahabad Bank	DMU 1
2.	Andhra Bank	DMU 2
3.	Bank of Baroda	DMU 3
4.	Bank of India	DMU 4
5.	Bank of Maharashtra	DMU 5
6.	Canara Bank	DMU 6
7.	Central Bank of India	DMU 7
8.	Corporation Bank	DMU 8
9.	Indian Bank	DMU 9
10.	Indian Overseas Bank	DMU 10
11.	Oriental Bank of Commerce	DMU 11
12.	Punjab & Sind Bank	DMU 12
13.	Punjab National Bank	DMU 13
14.	Sydicate Bank	DMU 14
15.	UCO Bank	DMU 15
16.	Union Bank of India	DMU 16
17.	United Bank of India	DMU 17
18.	State Bank of India	DMU 18

The input and output variables selected in this study for the Public Sector Banks is listed below in Table 2–3.

Table 2: Input Variables

Sr. No.	*Input Variables*	*Units*	*Notation*
1.	Deposits	Amount in Crores	IP1
2.	Fixed Assets	Amount in Crores	IP2
3.	Operating Expenses	Amount in Crores	IP3
4.	Staff	Number of Persons	IP4
5.	Paid-up capital	Amount in Crores	IP5

Table 3: Output Variables

Sr. No.	*Output Variables*	*Units*	*Notation*
1.	Total Income	Amount in Crores	OP1
2.	Investments	Amount in Crores	OP2
3.	Loans & Advances	Amount in Crores	OP3

This forms the data matrix which is the basis of the study. In this study, the data structure includes 5 input variables and 3 output variables. To summarise the characteristics of this data set, few statistical measures like Mean, Minimum, Maximum, Range and Standard Deviation of these input and output variables for Public Sector Banks are computed and presented in the following Table 4.

Table 4: Descriptive Statistics

	N	*Range*	*Minimum*	*Maximum*	*Mean*	*Std. Deviation*
Deposits	18	3151953.18	89667.55	3241620.73	502689.9872	720579.36942
Fixed Assets	18	37198.45	1240.83	38439.28	5917.0361	8533.07321
Operating Expenses	18	73315.66	1858.03	75173.69	10662.4983	16576.65202

	N	Range	Minimum	Maximum	Mean	Std. Deviation
Staff	18	239080.00	10368.00	249448.00	44304.8333	55003.75180
Paid-up capital	18	15828.19	608.80	16436.99	4002.2328	4182.93887
Total Income	18	293718.15	8826.92	302545.07	46351.0989	67140.33344
Investments	18	1022402.42	24552.10	1046954.52	163766.5422	230439.51242
Loans & Advances	18	2310328.56	14961.00	2325289.56	339278.9983	524592.02300

In the process of understanding this data set better, the author is interested in further examining the relationship between input and output variables. In view of this, the author attempted correlation analysis between the input and output variables, and the results are outlined below:

Table 5: Correlation Analysis

Input Variables		Output Variables		
		Total Income	Investments	Loans & Advances
Deposits	Pearson Correlation	1.000	0.997	0.998
	Sig. (2-tailed)	0.000	0.000	0.000
	N	18	18	18
Fixed Assets	Pearson Correlation	0.992	0.991	0.998
	Sig. (2-tailed)	0.000	0.000	0.000
	N	18	18	18
Operating Expenses	Pearson Correlation	0.996	0.994	0.993
	Sig. (2-tailed)	0.000	0.000	0.000
	N	18	18	18
Staff	Pearson Correlation	0.996	0.994	0.993
	Sig. (2-tailed)	0.000	0.000	0.000
	N	18	18	18
Paid-up Capital	Pearson Correlation	-0.288	-0.253	-0.316
	Sig. (2-tailed)	0.246	0.312	0.201
	N	18	18	18

From Table 5, it may be observed that the input variables considered, except for Paid-up Capital, have a significant relationship with the selected output variable. Though one input variable does not show a significant relationship with the output variables, Paid-up Capital is practically considered as an important input variable in Banking Sectors and plays a vital role in Data Envelopment Analysis and has thus been considered for the study.

Empirical Investigation

BCC – Efficiency Scores and Peer Weights

The application of BCC output oriented Model to Public Sector Bank data yielded the following results:

Table 6: Efficiency Scores and Peer Weights – BCC Model

DMU	Efficiency Score	Reference DMU Weights				
DMU 1	1.0467	λ_5 =0.4936	λ_7 =0.1179	λ_{11} =0.2610	λ_{16} =0.1276	
DMU 2	1	λ_2 =1				
DMU 3	1	λ_3 =1				
DMU 4	1.0515	λ_9 =0.3714	λ_{16} =0.5683	λ_{18} =0.0604		
DMU 5	1	λ_5 =1				

DMU	*Efficiency Score*	*Reference DMU Weights*				
DMU 6	1.0132	λ_3=0.4807	λ_9=0.3913	λ_{13}=0.0438	λ_{16}=0.0842	
DMU 7	1	λ_7=1				
DMU 8	1	λ_8=1				
DMU 9	1	λ_9=1				
DMU 10	1.0304	λ_2=0.4713	λ_5=0.1367	λ_7=0.2552	λ_{11}=0.0360	λ_{18}=0.1008
DMU 11	1	λ_{11}=1				
DMU 12	1	λ_{12}=1				
DMU 13	1	λ_{13}=1				
DMU 14	1.1279	λ_2=0.6554	λ_3=0.0415	λ_9=0.0853	λ_{11}=0.2078	λ_{18}=0.0101
DMU 15	1	λ_{15}=1				
DMU 16	1	λ_{16}=1				
DMU 17	1	λ_{17}=1				
DMU 18	1	λ_{18}=1				

From the Table 6, it is noted that 13 DMUs are efficient. The output targets of the inefficient DMUs are computed as a linear combination of peers and listed below:

Table 7: Targets for Inefficient DMUs

DMU	*Name of the Banks*	*OP1*	*OP2*	*OP3*
DMU 1	Allahabad Bank	20961.0024	84430.0521	149634.7536
DMU 4	Bank of India	51590.8543	179907.2901	392900.5404
DMU 6	Canara Bank	57498.6660	187225.6899	456379.3997
DMU 10	Indian Overseas Bank	21396.4218	81827.8602	138864.2334
DMU 14	Syndicate Bank	28155.9828	84555.1042	207990.5551

Table 7 portrays the target for the inefficient DMUs to increase their efficiency. The ranking of efficient DMUs based on the BCC model is furnished in Table 8 below:

Table 8: Ranking of DMUs

DMU	*Counts*	*Rank*
DMU 2	2	2
DMU 3	2	2
DMU 5	2	2
DMU 7	2	2
DMU 9	3	1
DMU 11	3	1
DMU 13	1	3
DMU 16	3	1
DMU 18	3	1

Here, it is observed that DMU9, DMU11, DMU16, and DMU18 receive Rank 1 and DMUs ranked 2 also have ties. The DMU8, DMU12, DMU15, and DMU17 are weak efficient as they do not serve as peers for the inefficient DMUs and are excluded from ranking.

VRS Super-Efficiency Scores

The super-efficiency score and peer weights for each DMU corresponding to Model V are calculated and presented in Table 9 below:

Table 9: Super-Efficiency Scores and Weights – VRS SE DEA Model

DMU	*Efficiency Score*	*Weights for Reference DMU*				
DMU 1	1.0467	λ_5=0.4936	λ_7=0.1179	λ_{11}=0.2609	λ_{16}=0.1276	
DMU 2	0.7706	λ_8=0.7732	λ_{12}=0.1886	λ_{16}=0.0382		
DMU 3	0.7927	λ_8=0.3721	λ_{13}=0.4237	λ_{18}=0.2042		
DMU 4	1.0515	λ_9=0.3714	λ_6=0.5683	λ_{18}=0.0604		
DMU 5	0.7820	λ_8=0.0865	λ_9=0.0900	λ_{12}=0.5623	λ_{15}=0.0971	λ_{17}=0.1641
DMU 6	1.0132	λ_3=0.4807	λ_9=0.3913	λ_{13}=0.0438	λ_{16}=0.0842	
DMU 7	0.8490	λ_{12}=0.1995	λ_{13}=0.2765	λ_{15}=0.5240		
DMU 8	0.5316	λ_2=0.2039	λ_{12}=0.7812	λ_{13}=0.0149		
DMU 9	Infeasible					
DMU 10	1.0304	λ_2=0.4713	λ_5=0.1367	λ_7=0.2552	λ_{11}=0.0360	λ_{18}=0.1008
DMU 11	0.9538	λ_2=0.2226	λ_3=0.0072	λ_8=0.3435	λ_9=0.3940	λ_{12}=0.0328
DMU 12	Infeasible					
DMU 13	0.7948	λ_3=0.5065	λ_9=0.2880	λ_{17}=0.2055		
DMU 14	1.1279	λ_2=0.6554	λ_3=0.0415	λ_9=0.0853	λ_{11}=0.2077	λ_{18}=0.0101
DMU 15	0.6372	λ_5=0.9878	λ_7=0.0122			
DMU 16	0.9115	λ_2=0.0856	λ_8=0.1081	λ_9=0.4603	λ_{13}=0.3400	λ_{18}=0.0060
DMU 17	0.7765	λ_5=0.3340	λ_8=0.2328	λ_{12}=0.4332		
DMU 18	0.2431	λ_3=0.8960	λ_9=0.1040			

From the above table, it may be observed that infeasible solution exists for DMU9 and DMU12. It is interesting to note that infeasibility occurs for the DMUs (DMU9 and DMU12) which are identified as efficient in BCC DEA Model. Besides, the above table indicates that there are 13 extreme efficient DMUs ($\phi^{SE*} < 1$) and 5 inefficient DMUs ($\phi^{SE*} > 1$). Also, it is identified that there are no efficient and weak efficient DMUs. The new facet target for each extreme efficient DMU in respect of their reference set are calculated and exhibited in Table 10 below:

Table 10: VRS New Facet Target

DMU	*OP1*	*OP2*	*OP3*
DMU 2	18690.0632	61818.8501	121557.3083
DMU 3	72939.5432	248937.2510	547038.0007
DMU 5	12668.7492	45490.6796	74204.3547
DMU 7	28637.8604	120991.8858	149967.1432
DMU 8	12427.5903	35313.6294	84817.1553
DMU 11	22502.7859	71166.9420	163698.0678
DMU 13	59559.8070	193741.8834	471260.6166
DMU 15	13316.4114	59202.0046	95575.9049
DMU 16	38730.6801	138922.7740	292820.0671
DMU 17	12851.5326	45530.4595	86655.6226
DMU 18	79898.8742	254489.4636	638949.0742

To demonstrate that the facet targets exhibit efficient stability, region DMU2 is considered and is presented in the following Table 11:

Table 11: DMU2 Reference Points

Variables		*Original Values*	*Reference Point*
IP1	Deposits	212609.38	212609.38
IP2	Fixed Assets	1482.51	1482.51
IP3	Operating Expenses	4639.04	4639.04
IP4	Staff	21436.00	21436.00
IP5	Paid-up Capital	3095.54	3095.54
OP1	Total income	22527.12	18690.06
OP2	Investments	61331.17	61818.85
OP3	Loan & Advances	157742.33	121557.31
ϕ^{SE}		0.7706	0.9999
Φ		1	1

In the above Table 11, it can be observed that the super-efficiency score of DMU2 remains extreme efficient if all the outputs of DMU2 are scaled down 0.7706 times proportionally with inputs unchanged. All extreme efficient DMUs can be interpreted in a similar way.

Condition for Infeasibility

Seiford and Zhu (1999) stated a necessary and sufficient condition for infeasibility through which the existence of infeasibility among the DMUs considered in this study has been verified and furnished in Table 12 below:

Table 12: Condition for Infeasibility

DMU	*Name of the Banks*	*h*(Infeasible Test)*
DMU 1	Allahabad Bank	0.4439
DMU 2	Andhra Bank	0.8370
DMU 3	Bank of Baroda	0.6579
DMU 4	Bank of India	0.2396
DMU 5	Bank of Maharashtra	0.7687
DMU 6	Canara Bank	0.5909
DMU 7	Central Bank of India	0.3097
DMU 8	Corporation Bank	0.8995
DMU 9	Indian Bank	**1.1515 ($h^* > 1$)**
DMU 10	Indian Overseas Bank	0.4022
DMU 11	Oriental Bank of Commerce	0.5114
DMU 12	Punjab & Sind Bank	**2.4382 ($h^* > 1$)**
DMU 13	Punjab National Bank	0.4654
DMU 14	Syndicate Bank	0.4832
DMU 15	UCO Bank	0.5940
DMU 16	Union Bank of India	0.2778
DMU 17	United Bank of India	0.8748
DMU 18	State Bank of India	0.6822

From the above table, it may be observed that the DMUs which are identified as infeasible under VRS SE Model satisfied the necessary and sufficient conditions for infeasibility ($h^* > 1$).

Sensitivity Analysis

Generally, sensitivity analysis is a crucial issue in DEA and hence an attempt has been made to perform sensitivity analysis in SE DEA model namely VRS *kth* specific output models. The SE scores related to VRS *kth* specific output DEA model are calculated and presented in the following section:

VRS kth Specific Output DEA Model

Next, the author attempted VRS *kth* specific output DEA Model. The results for the various combinations of *k* are calculated and presented in Table 13 below:

Table 13: VRS kth Specific Output SE Scores

DMU	$\Phi^{SE} = \alpha^0_{k=\{1,2,3\}}$	$\alpha^0_{k=\{1\}}$	$\alpha^0_{k=\{2\}}$	$\alpha^0_{k=\{3\}}$	$\alpha^0_{k=\{1,2\}}$	$\alpha^0_{k=\{1,3\}}$	$\alpha^0_{k=\{2,3\}}$
DMU 1	1.0467	1.1564	1.0887	1.0982	1.0792	1.0975	1.0467
DMU 2	0.7706	Infeasible	Infeasible	Infeasible	Infeasible	0.7706	Infeasible
DMU 3	0.7927	Infeasible	Infeasible	Infeasible	Infeasible	Infeasible	Infeasible
DMU 4	1.0515	1.0515	1.1397	1.0783	1.0515	1.0515	1.0736
DMU 5	0.7820	Infeasible	0.7365	Infeasible	0.7365	Infeasible	0.7643
DMU 6	1.0132	1.0132	1.1908	1.0560	1.0132	1.0132	1.0560
DMU 7	0.8490	Infeasible	0.8484	Infeasible	0.8484	Infeasible	0.8490
DMU 8	0.5316	Infeasible	Infeasible	Infeasible	Infeasible	Infeasible	Infeasible
DMU 9	Infeasible	Infeasible	Infeasible	Infeasible	Infeasible	Infeasible	Infeasible
DMU 10	1.0304	1.0607	1.0785	1.1288	1.0356	1.0492	1.0514
DMU 11	0.9538	Infeasible	Infeasible	Infeasible	Infeasible	0.9115	0.9538
DMU 12	Infeasible	Infeasible	Infeasible	Infeasible	Infeasible	Infeasible	Infeasible
DMU 13	0.7948	Infeasible	Infeasible	Infeasible	Infeasible	Infeasible	Infeasible
DMU 14	1.1279	1.1435	1.2810	1.1319	1.1408	1.1305	1.1297
DMU 15	0.6372	Infeasible	Infeasible	Infeasible	0.6372	Infeasible	Infeasible
DMU 16	0.9115	Infeasible	Infeasible	Infeasible	Infeasible	Infeasible	Infeasible
DMU 17	0.7765	Infeasible	0.7765	Infeasible	0.7765	Infeasible	0.7765
DMU 18	0.2431	Infeasible	Infeasible	Infeasible	Infeasible	Infeasible	Infeasible

The above Table 13 indicate that VRS *kth* specific output model reflects feasibility and infeasibility in respect of various combinations of k. A few observations are noted here.

DMU3, DMU8, DMU9, DMU12, DMU13 and DMU18 are infeasible in respect of all the VRS *kth* specific output models.

DMU2 and DMU11 are feasible with respect to the SE Model and kth specific model $\alpha^0_{k=\{1,3\}}$

DMU5, DMU7 and DMU17 are feasible with respect to the models $\alpha^0_{k=\{2\}}$, $\alpha^0_{k=\{1,2\}}$, and $\alpha^0_{k=\{2,3\}}$

Next, an attempt is made to construct the stability region for extreme efficient DMUs and the same is displayed in Table 14 below:

Table 14: VRS Output Stability Region

DMU	$\alpha^0_{k=\{1,2,3\}}$	$\alpha^0_{k=\{1\}}$	$\alpha^0_{k=\{2\}}$	$\alpha^0_{k=\{3\}}$	$\alpha^0_{k=\{1,2\}}$	$\alpha^0_{k=\{1,3\}}$	$\alpha^0_{k=\{2,3\}}$
DMU 2	$0.7706 < \alpha_{1,2,3} \le 1$	$\alpha_1 \le 1$	$\alpha_2 \le 1$	$\alpha_3 \le 1$	$\alpha_{1,2} \le 1$	$0.7706 < \alpha_{1,3} \le 1$	$\alpha_{2,3} \le 1$
DMU 3	$0.7927 < \alpha_{1,2,3} \le 1$	$\alpha_1 \le 1$	$\alpha_2 \le 1$	$\alpha_3 \le 1$	$\alpha_{1,2} \le 1$	$\alpha_{1,3} \le 1$	$\alpha_{2,3} \le 1$
DMU 5	$0.7820 < \alpha_{1,2,3} \le 1$	$\alpha_1 \le 1$	$0.7365 < \alpha_2 \le 1$	$\alpha_3 \le 1$	$0.7365 < \alpha_{1,2} \le 1$	$\alpha_{1,3} \le 1$	$\alpha_{2,3} \le 1$
DMU 7	$0.8490 < \alpha_{1,2,3} \le 1$	$\alpha_1 \le 1$	$0.8484 < \alpha_2 \le 1$	$\alpha_3 \le 1$	$0.8484< \alpha_{1,2} \le 1$	$\alpha_{1,3} \le 1$	$0.8490 < \alpha_{2,3} \le 1$
DMU 8	$0.5316 < \alpha_{1,2,3} \le 1$	$\alpha_1 \le 1$	$\alpha_2 \le 1$	$\alpha_3 \le 1$	$\alpha_{1,2} \le 1$	$\alpha_{1,3} \le 1$	$\alpha_{2,3} \le 1$
DMU 11	$0.9538 < \alpha_{1,2,3} \le 1$	$\alpha_1 \le 1$	$\alpha_2 \le 1$	$\alpha_3 \le 1$	$\alpha_{1,2} \le 1$	$0.9115 < \alpha_{1,3} \le 1$	$0.9538 < \alpha_{2,3} \le 1$
DMU 13	$0.7948 < \alpha_{1,2,3} \le 1$	$\alpha_1 \le 1$	$\alpha_2 \le 1$	$\alpha_3 \le 1$	$\alpha_{1,2} \le 1$	$\alpha_{1,3} \le 1$	$\alpha_{2,3} \le 1$
DMU 15	$0.6372 < \alpha_{1,2,3} \le 1$	$\alpha_1 \le 1$	$\alpha_2 \le 1$	$\alpha_3 \le 1$	$0.6372< \alpha_{1,2} \le 1$	$\alpha_{1,3} \le 1$	$\alpha_{2,3} \le 1$
DMU 16	$0.9115 < \alpha_{1,2,3} \le 1$	$\alpha_1 \le 1$	$\alpha_2 \le 1$	$\alpha_3 \le 1$	$\alpha_{1,2} \le 1$	$\alpha_{1,3} \le 1$	$\alpha_{2,3} \le 1$
DMU 17	$0.7765 < \alpha_{1,2,3} \le 1$	$\alpha_1 \le 1$	$0.7765 < \alpha_2 \le 1$	$\alpha_3 \le 1$	$0.7765 < \alpha_{1,2} \le 1$	$\alpha_{1,3} \le 1$	$0.7765 < \alpha_{2,3} \le 1$
DMU 18	$0.2431 < \alpha_{1,2,3} \le 1$	$\alpha_1 \le 1$	$\alpha_2 \le 1$	$\alpha_3 \le 1$	$\alpha_{1,2} \le 1$	$\alpha_{1,3} \le 1$	$\alpha_{2,3} \le 1$

Further, sensitivity analysis has been carried out for DMU13 based on the stability region constructed above:

Table 15: Sensitivity Analysis for DMU13

Variable	*Original Value*	$\alpha^0_{k=\{1\}}$	$\alpha^0_{k=\{2\}}$	$\alpha^0_{k=\{3\}}$	$\alpha^0_{k=\{1,2\}}$	$\alpha^0_{k=\{1,3\}}$	$\alpha^0_{k=\{2,3\}}$
IP1	703846.32	703846.32	703846.32	703846.32	703846.32	703846.32	703846.32
IP2	7239.07	7239.07	7239.07	7239.07	7239.07	7239.07	7239.07
IP3	11973.37	11973.37	11973.37	11973.37	11973.37	11973.37	11973.37
IP4	68520	68520	68520	68520	68520	68520	68520
IP5	1347.51	1347.51	1347.51	1347.51	1347.51	1347.51	1347.51
OP1	63074.16	63074.16 X 0.41	63074.16	63074.16	63074.16X 0.8098	63074.16X 0.01	63074.16
OP2	243754.14	243754.14	243754.14X 0.01	243754.14	243754.14X 0.8098	243754.14	243754.14X 0.01
OP3	471827.64	471827.64	471827.64	471827.64X 0.01	471827.64	471827.64X 0.01	471827 X 0.01
Standard CRS model	1	1	1	1	1	1	1
CRS SE	$\phi^{SE} =$ 0.7948	$\phi^{SE} = 0.7948$	$\phi^{SE} = 0.9443$	$\phi^{SE} = 0.7948$	$\phi^{SE} = 0.9815$	$\phi^{SE} = 0.7948$	$\phi^{SE} = 0.9443$
Output Specific Model	$\alpha^0_{k=\{1,2,3\}}$ =0.7948	$\alpha^0_{k=\{1\}} =$ Infeasible	$\alpha^0_{k=\{2\}} =$ Infeasible	$\alpha^0_{k=\{3\}} =$ Infeasible	$\alpha^0_{k=\{1,2\}} =$ Infeasible	$\alpha^0_{k=\{1,3\}} =$ 0.9998	$\alpha^0_{k=\{2,3\}} =$ Infeasible

It may be observed in Table 15 that DMU13 is efficient in BCC Model, extreme efficient in VRS SE Model and infeasible in specific output BCC models for different combinations of k, before and after data variations. Thus, OSR maintains the stability in efficiency classification. So, the extremely efficient DMU13 is stable and infeasible.

Conclusion

The author's primary focus in this paper is the sensitivity analysis of super-efficiency DEA Models. For the purpose of empirical research, data on Public Sector Banks that are active in India through 2019–20 period were taken into consideration. There are eighteen Public Sector Banks in the data structure. Every bank is regarded as a decision-making unit. In Public Sector Banks, three outputs and five inputs are taken into account. To assess the technical efficiency and ranking of DMUs, the author first used the conventional DEA model and the super-efficiency DEA model. Furthermore, a sensitivity analysis is performed on the DEA results. The following is a summary and presentation of the findings from the use of different DEA models:

The application of output oriented BCC reflects 13 banks were efficiently functioning. Indian Bank, in addition to Oriental Bank of Commerce, Union Bank of India and State Bank of India gets Rank 1 under BCC Model and so the tie occurs among the ranking of DMUs under BCC Model. Since tie occurs in ranking of DMUs, super-efficiency DEA model is applied. VRS SE DEA model reflects 13 extreme-efficient DMU and 5 inefficient DMUs. It may be noted that out of 13 extremely efficient DMUs, 2 DMUs namely Indian Bank and Punjab & Sind Bank have infeasible solution and the same is ensured by the infeasibility test suggested by Zhu (2003).

VRS kth specific output model highlights some of the results as feasible and infeasible and the following observations are noted: Bank of Baroda, Corporation Bank, Indian Bank, Punjab & Sind Bank, Punjab National Bank, and State Bank of India are infeasible in respect of all the VRS specific output models. Andhra Bank and Oriental Bank of Commerce are feasible with respect to the SE Model and kth specific model. Bank of Maharashtra, Central Bank of India, and United Bank of India are feasible with respect to the models. Sensitivity Analysis done on Punjab National Bank showed that the bank is efficient in BCC Model, extreme efficient in VRS SE Model and infeasible in specific output BCC models for different combinations of k, before and after data variations. Thus, OSR maintains stability in efficiency classification. Thus, sensitivity analysis can be performed for the other banks as well to predict the outcome of a specific action when performed under certain conditions.

By putting the model to the test in a variety of conditions, sensitivity analysis gives legitimacy to any kind of financial model. When testing the sensitivity of the dependent variables to the independent factors, financial sensitivity analysis gives the analyst a lot of leeway in terms of boundaries. Sensitivity analysis facilitates decision-making. The model is used by decision-makers to determine how sensitive the output is to variations in particular factors. As a result, the analysis may assist in drawing concrete conclusions and play a crucial role in helping banking sectors reach the best judgement.

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