Data Envelopment Analysis – Is BCC model better than CCR model? Case of Indian Life Insurance companies

Prof Pradeep Pai[1]
Bilal Mustafa Khan[2]
T. Kachwala[3]

Abstract

In our earlier paper, "Data Envelopment Analysis (DEA) – Application at NMIMS – SBM, a Leading AACSB Accredited Indian Higher Education Business School" published in NMIMS Management Review, 2019 University Day edition, the authors had explained the concept of DEA in Services Operations, using the basic Charnes Cooper and Rhodes (CCR) model. The application was tested on NMIMS considering two input variables and two output variables. We will see later why the CCR model was appropriate for the NMIMS application. The objective of this paper is to explain the limitations of the basic CCR model when efficiency is computed for different business establishments in the same business, unlike different branches or units of one organization. In the earlier research paper, the DMUs were divisions of NMIMS and thus, homogeneous to a large extent belonging to the same organization. In the present case, the DMUs are separate business units and we propose the Banker, Charnes and Cooper (BCC model) for analysis, which is superior to the CCR model for this application. Besides explaining why the BCC model is superior to the CCR model, we also highlight other considerations in various DEA models and situations under which they are applied. Some of the considerations that necessitate a change in the basic CCR model approach are:

a) Weightages attached to each of the input and output factors,
b) Constant return to scale or variable returns to scale,
c) Input orientation or output orientation, or non-oriented considerations,
d) Qualitative factors like competence, etc., which are difficult to quantify or data that requires the use of the ordinal scale.

Qualitative factors like faculty competence are measured either on a Likert scale or are represented by some quantitative surrogate such as students' performance in term-end examinations or the class participation scores. We may also have issues with data timing; for instance, placements happen in trimester V whereas overall performance is a combination of all six trimester efforts. In such cases, we end up relying on rough estimates of the factual data value, which can result in incorrect conclusions. Another limitation is that the placement performance could be a factor of specialization discipline like Marketing, Finance, Operations, etc., and the number of students taking these disciplines across ten DMUs, which may be dissimilar. Moreover, the placements may also be a factor of the disciplines in demand in a particular year (Cook, Hababou, Tuenter, 2001). In situations such as those described above, the data for

1 Associate Professor – School of Business Management, NMIMS.
2 Professor, Department of Business Administration, Aligarh Muslim University, Aligarh, India
3 Professor, School of Business Management, NMIMS

certain influence factors (inputs and outputs) may better be represented as rank positions in an *ordinal scale* rather than numerical scale. In our example, the faculty on the basis of competence could be grouped as "high" competence, "medium" competence or "low" competence. In some other cases, one may be able to provide a complete rank ordering of the DMUs on similar factors.

This research paper examines the working of the BCC model (Pure Technical Efficiency, PTE) and highlights the essential limitation of the CCR model (Overall Technical Efficiency, OTE) if the DMUs are scale differentiated as a result of being different entities.

Practical Implications: DEA analysis is used to evaluate the efficiency of most service organisations by identifying the various DMUs and a common set of inputs and outputs. Whether these inputs and outputs are exhaustive enough would never be known and therein lies the first set of imperfections. The second set of imperfections can be what is actually contributing to the inefficiency in certain units. Is it the improper conversion of inputs into outputs (PTE) or is it the size of operations that is the matter, termed Scale efficiency (SE). While using the CCR model, size imperfections are ignored and any unit, which has 4 times the inputs and 4 times the output, is also considered efficient (OTE). The BCC model takes the size infractions into account (rather ignores it) and computes the pure technical efficiency, and is thus best suited when the DMUs are different firms or organisations operating in similar businesses. A lack of homogeneity is not a problem for BCC. At times, we are keen to know the contribution of Scale Efficiency (SE) in the overall efficiency. The CCR model and BCC model inefficiency comparisons will help in also identifying the SE. We come across many DEA analyses using the CCR model, but unless the homogeneity conditions are considered, the CCR model should not be used.

Originality / Value: This DEA analysis of the Indian life insurance companies covering the private and public sector enterprises highlights the inappropriateness of the commonly used CCR model. The paper also shows how using the CCR model would have set wrong and unachievable targets for betterment of inefficienct DMUs. The recommended BCC model for this data and applications correctly identifies the target for improvement of the inefficient units. It also describes the reasons for the CCR model being ineffective in the present case and analyses the reason for differences between the CCR and BCC models. In the BCC application, we once again focus on the input orientation rather than on the output orientation. The reasoning remains the same as in our earlier research paper, and that is, it is more feasible to set targets for the inputs in a service industry than attempting to set targets for outputs.

Keywords: *Benchmarking, DEA, CCR, BCC, SE, OTE, PTE, lambda / shadow price, efficiency.*

1. Introduction:

In management practice, mathematical programming is used to evaluate the various alternatives and then choose the best option. This mathematical programming is effective as a planning tool. In the case of efficiency analysis using DEA, post facto evaluations are made and therefore, DEA is more of a monitoring and controlling tool rather than a planning tool. In our research paper, we have focused more on this DEA applicability aspect, its variation and impact of such variations, rather than a focus on mathematical aspects found in theoretical papers. Concrete theoretical boosts as in exacting sciences like engineering are not available for DEA applications and they get replaced with weaker support from disciplines like economics. This results in satisfying one with weaker measures like relative efficiency rather than a stronger and more correct result obtained from a stronger theory.

Efficiency measurement has been generating much interest in contemporary times for evaluating efficient Decision Making Units (DMUs) versus those DMUs that are not efficient enough. The business cycles change so fast that in a blink of an eye, an otherwise successful business idea becomes redundant with only cash burn. Many services organizations like Tiny Owl, Food Panda, Local Baniya, MERU, and others are closing operations, or have already closed down.

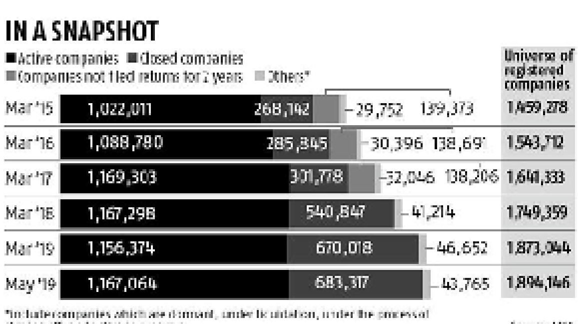

Exhibit 1: Data of Closed Companies in India.
Source: Ministry of Corporate affairs (MCA)

Exhibit 1 gives a picture of the percentage of companies (product as well as services) closing down in India over the past 4 years and this number is a staggering 32%. As per Farrel (1957) "*The problem of measuring the productive efficiency of an industry is important to both the economic theorist and the economic policy maker. If the theoretical arguments as to relative efficiency of different economic systems are to be subjected to empirical testing, it is essential to be able to make some actual measurements of efficiency. Equally, if economic planning is to concern itself with particular industries, it is important to know how far a given industry can be expected to increase its output by simply increasing its efficiency, without absorbing further resources*". One of the reasons Farrell attributed to the failure of efficiency measurement is the difficulty to combine the multiple inputs and outputs into any satisfactory measure of efficiency.

Almost twenty years after Farrell's seminal work in the measure of efficiency, Charnes, Cooper and Rhodes published a research paper on DEA Analysis, "Measuring the efficiency of decision-making units" in European Journal of Operational Research1978, 2(6): 429~444. Their proposed model is now referred to as the CCR model. Over the next 40 years, there was a rapid and vigorous growth in DEA applications and in their 2017 paper, Ali Amrouznejad and Guo-liang Yang list down 2,974 such DEA articles / research papers highlighting the use of DEA analysis, most of them being published in the top 20 research journals.

The original idea behind DEA was to provide a method wherein a set of similar DMUs can be segregated as efficient and inefficient, relative to each other. This measurement of relative efficiency could be used to set a target of betterment for the inefficient units, and as a last resort, decide on the DMUs to be closed. A 4 x 4 DEA strategy matrix with one axis being efficiency and the other axis being productivity is then constructed. Exhibit 2 presents this DEA strategy matrix. The set of DMUs that are efficient then form the efficiency frontier for other DMUs to follow and consider as a benchmark. As the benchmarking is relative, the nuances of the business, which are common for all the DMUs, is well captured. Although the DEA approach is not without limitations, it does provide a ball-park figure for improvement of the inefficient DMUs by comparing their performance with the efficiency frontier, established by efficient DMUs.

The DEA strategy matrix identifies those DMUs which need to be closed down. Surprisingly, highly efficient DMUs fall in this category to be closed down because their profit contributions are low. This two-axis approach helps in identifying DMUs which do not make business sense and those DMUs which need some interventions, besides those DMUs which could be considered as the benchmark DMUs. Benchmark DMUs are those DMUs whose technical efficiency is the highest. It must be noted that the problem DMUs are not the ones that need to be closed down. Rather these are the DMUs which, with little interventions, can be potentially high performing stars.

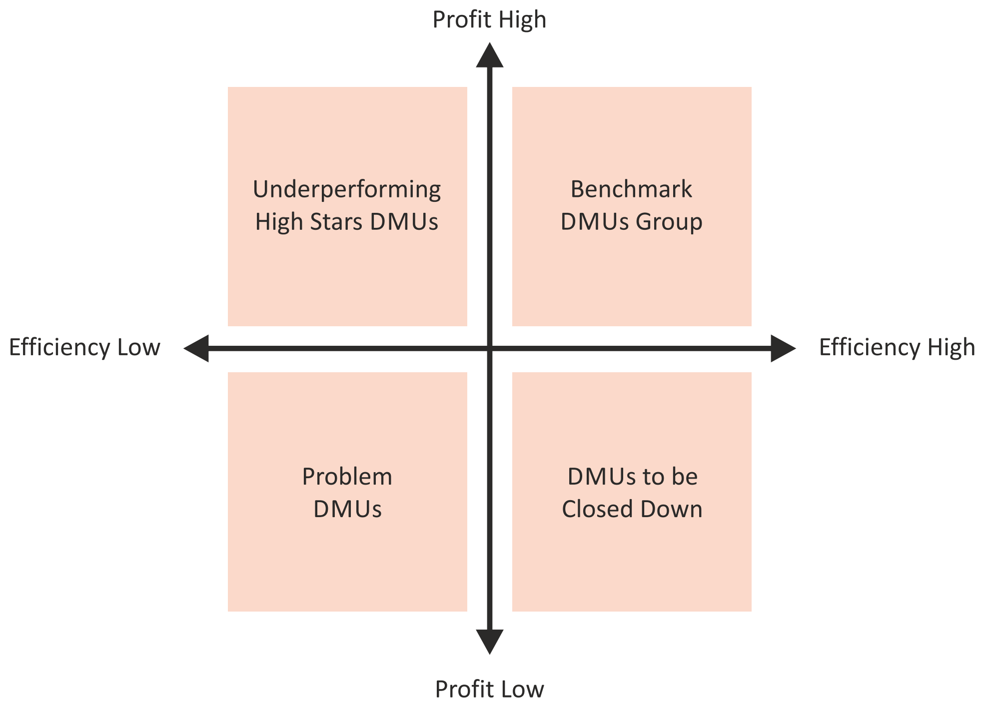

Exhibit 2: DEA Strategy Matrix

The DEA approach for technical efficiency measurements is most applicable for services, and as the global economy continues to develop, services and services sector would continue to play a key role in the economic growth. DEA and DEA applications would therefore be extant and growing in this global economy as a tool for measuring service operations' technical efficiency. Although DEA is not a robust parametric technique like multiple regression analysis, the simplicity and ease of application is most suited for rough cut efficiency estimations.

2. Literature Review and Observations:

Gurumurthy Kalyanaram, (October 2019) in the editorial of NMIMS Management Review Journal, speaks about the fifth generation (5G) network, emerging new global economic and market order, and Huawei and the requirements for their success. He also speaks about the advent of crypto currency, block chains in economy and commerce. Implicit in the narrative is that these services have to be technically efficient for sustainability of their operations. DEA is one such technique that will help in identifying the sustainability of these 5G services offered by the various service providers across the globe.

Pradeep Pai, et al (2019) in their research paper 'Data Envelopment Analysis (DEA) – Application at NMIMS – SBM, a Leading AACSB Accredited Indian Higher Education Business School' have extensively spoken about the CCR model and the Overall technical efficiency. The paper also highlights the limitation of the applications of the DEA techniques in practice. Although it does not discuss the BCC model, some of the limitations highlighted in the research paper could be addressed using the BCC model.

Andreas Dellnitz, Andreas Kleine, Wilhelm Rodder (2018) speak about the choice of CCR or BCC model for any application and suggest that the inefficiencies using both the models could be considered. The results could then be used to find out the scale efficiency (SE). The authors believe that activity scaling under constant BCC influences CCR efficiency, and constant CCR influences the BCC efficiency. As per the authors, such mutual effects help the DMU resize their activities.

Gordhan K. Saini, S. K. Pandey, Archana Singh, Gurumurthy Kalyanaram (2018) in their research paper "Role of Empathy and Customer Orientation in Job Satisfaction and Organizational Commitment in Indian Stock Markets" examined the concept of customer orientation in the services sector. The paper investigates the reasons for the customer's unhappiness after an interaction with the service personnel. A measure for the dissatisfaction level and setting a benchmark for the service personnel is referred to in this paper.

Siti Fatimah &Umi Mahmudah (2017) opine that the *VRS* model of DEA gives better results than the *CRS* model of DEA. In their research covering 34 provinces of Indonesia for school efficiency, the *CRS* model identifies 12 provinces (35.29%) as efficient whereas the *VRS* model identifies 16 provinces (47.06%) as efficient.

Fatemeh Afshar Zeydabadi, Ali Namazian, Roghayyeh Montazer (2015) in their research paper, perform a comparative study of the CCR and BCC models in assessing financial performance of the drug industry in Iran. The authors opine that the financial statements can be misrepresented and are not always reflective of the best health of the business unit. Using the concept of the Window Data envelopment analysis, the authors processed financial ratios concurrently for different time factors. The authors conclude that there is a meaningful difference in efficiency readings using the CCR and the BCC models for window DEA.

Dr. T Rajasekhar, Dr. Malabika Deb (2014) measured the difference in efficiency between the input and the output oriented DEA. The authors found no meaningful differences in the efficiency on the basis of orientation and found that ports like JNPT, Kandla, Mormugao and Ennore were observed as efficient ports by both the orientation methods.

Mehdi Toloo, Soroosh Nalchigar (2009) speak about the applicability of the BCC model and its advantages over the basic CCR model. To prove their point that the BCC model is better, a case involving 19 facility layout decisions is analysed. They stress the fact that the BCC model is most suitable in case of variable returns to scale.

Meilisa Malik, Syahril Efendi, Muhammad Zarlis

(2008), in their paper Data Envelopment Analysis (DEA) Model in Operation Management, speak about the application of CCR, BCC and SBM DEA models for quality management efficiency determination. The paper addresses the requirement of quality upgradation targets without losing focus on business competitiveness.

Barros, Carlos & Dieke, Peter (2007) in their research paper on Performance evaluation of Italian airports using the DEA analysis, address the financial and operational performance for the period 2001~2003 using panel DEA approach.

Kristina Vincova (2005) speaks about the application of the various DEA techniques, especially the CCR and BCC model. The paper also speaks about Tonen SBM (Slack Based Model) and super SBM models that work on the concept of super efficiencies. The paper concludes by stating that possible ways of measuring the efficiency in different situations were considered.

V V Podinovski (2004) speaks about a hybrid approach to DEA analysis, that combines the advantages of *VRS* model and the *CRS* model. As per the author, the *CRS* measure requires the proportionality assumption for inputs and variables whereas in case of the *VRS* model, this information is effectively ignored, often resulting in overestimating the efficiency of the DMUs. The paper then proposes a hybrid model which combines the assumptions of the *CRS* with respect to the selected sets of inputs and outputs, and preserves the *VRS* assumptions with respect to the other indicators.

3. The Models:

3.1 Constant returns to scale (CRS) model:

Consider a set of k DMUs, with each DMU j (j = 1, 2, 3….k) using m inputs $v_{1,}$ $v_{2,}$ $v_{3,.....}$ v_m and generating n outputs, $u_{1,}$ $u_{2,}$ $u_{3,}$….. u_n then efficiency e_j of DMU$_j$ will be the ratio,

$e_j = \frac{\sum_n Ci\ uij}{\sum_m Wi\ vij}$ where C_i and W_i are multipliers or profit for all the outputs and multipliers or the cost for all inputs, respectively. The *technical efficiency* under the CCR model for DMU$_A$ is therefore, e_A = Max $\frac{\sum_n Ci\ uiA}{\sum_m Wi\ viA}$

subject to $\sum_i Ci\ uij - \sum_i Wi\ vij \leq 0$, for all j

The above model is referred to as *input-oriented* model though it can also be used for *output-oriented* problems as well. It is assumed that in most cases, the inputs being integral to the business / system can be within the control of the decision maker, whereas the outputs, depending on various externalities, are outside the purview of the decision maker. As such, any efficiency target for outputs would be ill advised.

3.2 The variable returns to scale (VRS) model:

In the case of variable return to scale, the returns are not proportionate to increase in efforts. For example, the cost of buying one unit and the cost of buying ten units is not the same, as the increase in quantity results in reduced price. So, if a product costs Rs.50/- per unit and a bulk discount of 20% is available on the purchase of ten units, the net buying cost of ten units is not Rs.500/- but Rs.400/-. This reduction of Rs.100/- is not due to any extra effort, but due to scale. The VRS model was the extension of work done by Banker R D, Charnes A, and Cooper WW in the year 1984. The BCC ratio model includes an additional variable in the CCR formulation that results in an additional convexity constraint on the Lagrange multiplier (shadow price). Exhibits 3 and 4 explain the concept of VRS.

The *technical efficiency* under the VCR model for DMU$_A$ is therefore,

e_A = Max $\frac{\sum_n Ci\ uiA - uA}{\sum_m Wi\ viA}$, subject to

$\sum_i Ci\ uij - u_A - \sum_i Wi\ vij \leq 0$, for all j and u_A unrestricted in sign.

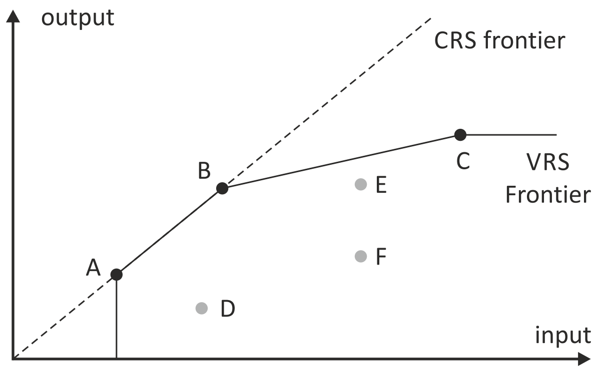

Exhibit 3 – Variable Return to Scale Efficiency frontier

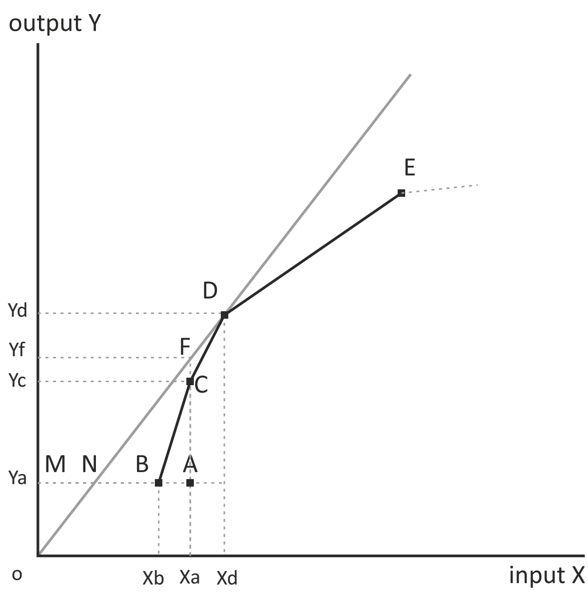

Exhibit 4 – Technical and Scale efficiencies

Technical Efficiency (for Input control) = $\frac{MB}{MA}$, Scale Efficiency (for Input Control) = $\frac{MN}{MB}$

Technical and Scale Efficiency (for Input Control) = $\frac{MN}{MA}$

3.3 The additive model:

In the case of *CRS* model and *VRS* model, we can assume the model to be radial, by which we mean that for input orientation, the outputs remain constant and likewise, for output orientation, the inputs remain constant. Charnes A, Cooper, W W, Golany B, Seiford L, Stutz J (1985) introduced the additive or Pareto – Koopmans (PK) model, that addresses both the input orientation and the output orientation. Exhibit 5 explains the additive model and comparison with the input orientation and the output orientation. The convexity conditions ensure that we are using the *VRS* model.

A DMU is additive efficient (also called PK efficient) when all the slacks equal to zero and when it is *VRS* efficient.

3.4 Slacks based measures:

The various inputs and outputs may be measured in non-commensurate measures. The output might be in monetary equivalent and the input might be labour hours, and thus, a simple sum of slacks may not be practical. The slacks based measure (SBM) developed by Tone in 2001 is invariant to the units of measurement and is unchanging in increasing each input and output slack.

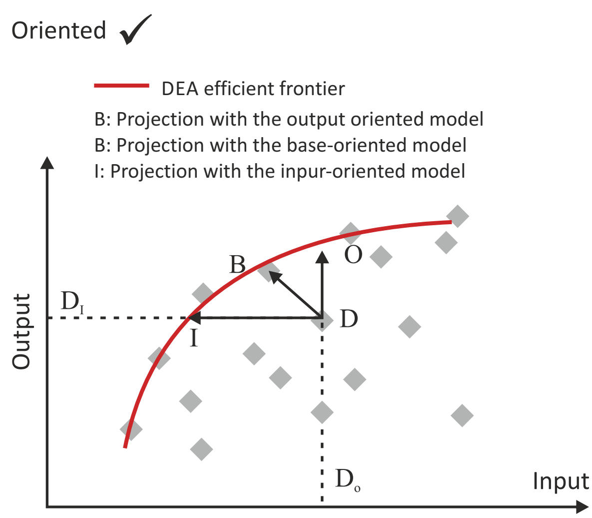

Exhibit 5: Additive model projection with VRS.

3.5 The Russell measure:

The Russell measure model is equivalent to Tone's SBM model. It was first named by Fare and Lovell in 1978 and revisited by Pastor et al, in 1999 and referred to as enhanced Russell measure.

3.6 Special consideration regarding the status of variables: The originally conceived DEA model involves the generation of *u* outputs using *v* inputs. In a structure like this, when all the inputs are projected radially to the efficient frontier, we expect the variables to be quantitative. In a certain setting, however, qualitative variables may be present. For a factor such as faculty competence, one may be only able to provide the ranking of inputs from best to the worst. Although these factors can be quantified using a Likert scale, such quantification is superficially forced as a modelling convenience. At times, we might also encounter *non-discretionary* variables, by which we mean the variables that are not directly within control of the management. In the case of life insurance companies, fixed expenditures like rent, utilities, etc. cannot be proportionately reduced unlike staff employed, when compared with the benchmark DMUs. At times, we have some *non-controllable* variables like minimum staff strength in a DMU, which cannot be further reduced to increase the technical efficiency of that DMU. Likewise, there may be outputs that cannot be controlled. The life insurance business has also got social benefit responsibilities and must have a network of branches in remote areas for customer accessibility convenience. How can this DMU be technically efficient when the social responsibility drives the business decision?

4. Criticism of the DEA technique and how we have addressed the same in this paper

Besides the generic criticism to DEA that the outputs can be tailored and that the DEA is not a rigorous parametric technique, we identify a few important criticisms and some ways to circumvent the same.

4.1 – The entire focus in DEA analysis is the inefficient DMUs and suggested targets of inputs or outputs (depending upon the orientation of research) for the improvement of these inefficient DMUs. If we look at the efficient DMUs, they are still very different in their consumption of inputs or their outputs. Is there therefore, nothing to be learned for efficient DMUs from closely examining the other efficient DMUs? The DEA technique is silent here and the only time when an efficient DMU gets a benchmark "target" is when the inefficient DMUs become super-efficient rendering the initially efficient DMU inefficient. As per author *Thomas R Sexton,* it is not uncommon to have a large number of DMUs to be marked as efficient in DEA analysis. In our example, 11 DMUs were found to be efficient out of 22 DMUs, which meant that for the 11 efficient DMUs, there is actually no benchmark for improvement on any inputs. A linear programming problem with (N + 1) constraints where N is the number of DMUs operates in $U + V$ dimensions (one each for every input and every output). If the dimensions are many compared to the constraints, then many DMUs will be rendered efficient simply because they would be lying near the efficiency frontier. One way to circumvent this problem is by increasing the number of DMUs and if the same is not possible (as in our present case, where only 22 private life insurers are operating in India), we must reduce the number of inputs and outputs being considered.

4.2 – As discussed in the section above, a related problem is that we cannot decide whether the technically efficient DMU is producing a socially optimum output mix by using the least cost technology. Thus, DEA cannot be used to comment on a DMU's price efficiency, which would lead to a situation wherein the DMU is technically efficient, but price inefficient. This might also lead to a situation where the technically inefficient DMU is manufacturing goods at a lower price. So, situations where price efficiency is more important than technical efficiency, DEA analysis may actually be a disadvantage. However, in our case of IRDAI private life insurers, we are more concerned with the technical efficiency rather than the price efficiency and hence, DEA analysis in our research paper is apt.

4.3 – The DEA technique has a weakness in that it does not undervalue quality inputs in determining efficiency. For example, if some of the Life Insurance companies appoint only well qualified staff with education from premier institutes while other companies appoint staff from lower rung institutes, the efficiency of the first set of companies will be higher. There must be a factor to negate the quality superiority of inputs and outputs across DMUs. In our IRDAI data, we have not made any such alienation and pre-suppose that all the staff employed have similar educational qualifications.

4.4 – Misspecification errors: Although misspecification of model parameters and the related issues are generic problems for all models, some models are more sensitive than others. Median based estimation techniques are less susceptible to coding errors than the mean based estimation techniques, which are more susceptible. As per *Charnes*, though DEA is a free form technique, it can be very sensitive to model specifications and data errors. Further, DEA analysis is based on extremal points and thus is more sensitive to the specification of modelling. If an efficient DMU was wrongly coded or misquoted, then the resultant isoquant line would be incorrect and the DMUs shown as inefficient may have actually been efficient. Further, the efficiency improvement targets would also be incorrect. If the coding or data error was with respect to the inefficient DMU, then the ill-effects of miscoding would be limited to the inefficient DMU only. To conclude, we can say that data errors will have broader though smaller quantitative impacts when mean based methodologies are used. However, in case of extremal methodologies like DEA, coding or data errors will have a magnifying effect. In our case, the data is provided by IRDAI, which is a regulatory authority monitoring the business of life insurance in India, and hence, data validity is not a problem.

4.5 – Variable Selection: A major shortcoming of the DEA technique is the inability to link statistically or causally the inputs with the outputs for the DMUs. There is no way of assessing the relative strengths of different model specifications as the calculated efficiency explains the extremal relationships under any specifications. With this, we mean that whether to consider 4 inputs or 5 inputs, or 5 outputs or 6 outputs can never be assessed, unlike in case of regression where we have adjusted R^2 telling us whether an extra independent variable was helpful or not. What criteria do we choose amongst alternative model specifications to include or exclude inputs or outputs from the analysis? The inclusion of irrelevant factors or noise in a DEA application will produce efficiency results which cannot be distinguished from some theoretically correct model specifications. A corollary could also be that any DMU could be doctored into looking efficient by some choice of inputs and outputs, not necessarily correct. In our IRDAI data analysis, we are unsure whether we are also guilty of similar excesses having selected the inputs and outputs as available. However, as the theme of the research paper is to highlight the advantages of the *VRS* model over the *CRS* model, and not in setting the efficiency benchmarks for the DMUs, we reckon that the analysis we have done is acceptable.

5 – Efficiency in Service Organizations:

5.1 – As per the Reserve Bank of India, RBI (FY 2017 data), the Indian banking industry comprises 27 public sector banks, 49 foreign banks, 56 region rural banks, 1,562 urban cooperative banks and 94,384 rural cooperative banks. The increase in deposits over the past ten years was at a CAGR of 11.66% and the increase in lending over the past ten years was at a CAGR of 10.94%. However, the nationalized banks are facing some of the following problems:

1) Losses in rural branches.
2) Large overdue in most branches.
3) Large non-performing assets.
4) Lack of advances to priority sector.
5) Competition from non-banking financial companies (NBFCs).

6) Competition from foreign banks.
7) Widening gap between the objectives of nationalization and performance of nationalized banks.
8) Large number of employees and therefore, advances in technology not helping in reducing the employee wage bill.
9) Unionization of labour resulting in customer inconveniencies.
10) Political pressures.

As a result, the performance (efficiency) of the banks and bank branches (DMUs) becomes very important. When the performance measurement is inter-bank, then we suggest the BCC model, and when the performance measurement is intra-bank, we believe that the CCR model would work best. This is because the BCC model ignores the scale inefficiency, which is required when banks of different sizes (or scales) get compared. However, the BCC model overestimates the technical efficiency of the DMUs as a result of ignoring the scale inefficiency. So, when the scale inefficiency is not an issue (for intra-bank analysis) we should prefer the CCR model. This aspect would be explained in detail when we compare the technical efficiency of the life insurance companies on the basis of published IRDAI data in the next section.

5.2 – Insurance Regulatory and Development Authority of India (IRDAI): The mission statement of this regulatory authority (as available on their website) reads the following:

- To protect the interest of and secure fair treatment to policyholders;
- To bring about speedy and orderly growth of the insurance industry (including annuity and superannuation payments), for the benefit of the common man, and to provide long term funds for accelerating growth of the economy;
- To set, promote, monitor and enforce high standards of integrity, financial soundness, fair dealing and competence of those it regulates;
- To ensure speedy settlement of genuine claims, to prevent insurance frauds and other malpractices and put in place effective grievance redressal machinery;
- To promote fairness, transparency and orderly conduct in financial markets dealing with insurance and build a reliable management information system to enforce high standards of financial soundness amongst market players;
- To take action where such standards are inadequate or ineffectively enforced;
- To bring about optimum amount of self-regulation in day-to-day working of the industry consistent with the requirements of prudential regulation.

The IRDAI is a constituted body with a directive to regulate and develop the insurance industry in India, which covers both Life Insurance and non-Life Insurance businesses. As per the latest information available on their website, presently, there are 31 general insurance companies and about 24 life insurance companies operating in India. Although the history of insurance business predates the industrial revolution, in India the Insurance Act was amended in 1968 to regulate investments and set up minimum solvency ratios. Further, in the year 1972, the General Insurance Business Act was passed resulting in the insurance businesses being nationalized with effect from 1st January 1973.

The IRDA opened up the insurance business to non-government organizations in August 2000. Foreign companies were allowed ownership of up to 26% which as of now, stands revised to 49% ownership. The IRDAI has the power to frame regulations under Section 114A of the Insurance Act, 1938 and has over the past years, framed various regulations to protect policyholders' interests. The insurance companies are obliged to file monthly data in the prescribed format with the regulatory authority, without any exceptions. For the purpose of our research, we have taken the latest (September 2019) published data on 22 life insurance companies from the IRDAI website.

5.3 – Life Insurance Business in India: Life insurance in India has been synonymous with Life Insurance Corporation of India (LIC) and LIC continues to be the industry leader even today. With the opening up of the insurance business, prominent private sector life insurers like Aditya Birla Sun Life, Aegon Life, Aviva Life, Bajaj Allianz Life, Bharti Axa Life, Canara HSBC OBC Life, DHFL Pramerica Life, Edelweiss Tokio Life, Exide Life, Future Generali Life, HDFC Life, ICICI Prudential Life, IDBI Federal Life, India First Life, Kotak Mahindra Life, Max Life, PNB Met Life, Reliance Nippon Life, SBI Life, Shriram Life, Star Union Dai-ichi Life, and Tata AIA Life opened up businesses in India. For our efficiency studies, we have considered 21 private sector life insurance companies and one government controlled company, namely, the Life Insurance Corporation of India.

In Exhibit 6, we list down the inputs and outputs for 22 life insurance companies operating in India. The inputs include:

1) Direct Selling Agents,
2) Number of branches in the year 2017 ~ 2018.
3) Years in Business in India.
4) Claims settled within the first 30 days &
5) Total claims settled in one year.

The outputs considered were:

1) First year premiums received (in Rs. crores)
2) Number of policies / schemes issued in the year.
3) Number of lives covered &
4) Sum assured in Rs. crores.

DMU's	Input 1 Direct Selling Agents	Input 2 No of Branches 2017 - 2018	Input 3 Years in Busness	Input 4 Claims settled within 30 days	Input 5 Total Claims Settled in Full Year	Output 1 First Year Premiums Rs Crores	Output 2 No Of Policies / Schemes	Output 3 No Of Lives Covered	Output 4 Sum Assured Rs Crores
Aditya Birla Sun Life	91,720	452	19	4490	5252	1065	94,692	11,25,933	80,424
Aegon Life	5,739	84	11	529	530	36	10,355	58,842	14,217
Aviva Life	16,431	93	17	1051	1056	74	6,800	1,63,182	3,212
Bajaj Allianz Life	70,763	631	18	10218	13176	1728	1,05,663	1,24,10,137	98,859
Bharti Axa Life	28,638	188	13	748	860	343	1,03,039	34,115	11,703
DHFL Pramerica Life	12,318	117	11	496	572	252	17,495	49,45,496	24,195
Edelweiss Tokio Life	31,031	123	8	144	180	113	26,559	79,225	12,644
Exide Life	46,126	217	18	2722	3250	299	71,697	7,19,980	25,866
Future Generali Life	11,890	104	12	909	1202	285	22,102	2,79,774	29,154
HDFC Life	77,048	414	19	10744	12289	6700	3,49,428	2,34,02,577	3,53,534
ICICI Prudential Life	1,51,563	503	19	10816	11216	4214	2,94,501	1,06,47,366	2,26,747
IDBI Federal Life	10,763	62	12	1006	1068	204	21,087	47,075	4,760
India First Life	1,660	29	10	1395	1626	645	68,340	17,99,591	58,331
Kotak Mahindra Life	94,688	228	18	2407	2881	1688	98,491	62,39,212	73,684
Max Life	56,968	210	19	8545	10152	1793	2,11,920	21,74,032	1,05,108
PNB Met Life	6,452	110	18	3708	3726	616	73,420	13,70,808	71,840
Reliance Nippon Life	65,099	746	18	7854	8553	379	85,605	7,20,803	10,993
SBI Life	1,08,261	825	17	16046	18274	5929	5,61,158	19,24,471	1,73,227
Shriram Life	4,498	609	14	2511	2524	253	90,587	11,58,322	18,242
Star Union Dai-ichi Life	4,757	102	11	948	1145	208	23,893	5,59,192	14,234
Tata AIA Life	26,963	182	17	2793	2793	1043	1,49,032	2,24,470	95,350
LIC of India	11,48,811	4908	63	735154	856622	77221	67,96,389	96,12,429	2,22,828

Exhibit 6: Input and Output data for 21 private and 1 government life insurer

Using the Shiny DEA app, the efficiency results are obtained and are as given in Exhibit 7. The CCR model (Constant return to scale) for both input and output efficiency and the BCC model (Variable returns to scale) for both input and output are considered. One of the dilemmas facing the analyst is whether to use the input orientation model (wherein we focus on better utilization of the inputs) or to use the output orientation model (wherein we focus on the targets and outputs achieved). It is always within our control to better utilize the resources or inputs, and hence, setting a target for the inputs or performance is feasible. However, as the outputs depend on many extraneous factors, they are not within our control. Setting targets for outputs, therefore, is not feasible. With each insurer wanting to convey a positive impression about their performances, outputs like lives covered or sum assured can, at times, be misleading. It is observed that the inefficiency measure is more than 1, which is very intriguing. It is possible because of anomalies related to scales and / or consideration of output measures.

Sr No	DMU's	CCR Model Output	BCC Model Output	CCR Model Input	BCC Model Input
1	Aditya Birla Sun Life	0.497	0.898	0.497	0.462
2	Aegon Life	0.311	0	0.311	0
3	Aviva Life	0.865	5.441	0.865	0.242
4	Bajaj Allianz Life	0.425	0.707	0.425	0.231
5	Bharti Axa Life	0	0	0	0
6	DHFL Pramerica Life	0	0	0	0
7	Edelweiss Tokio Life	0	0	0	0
8	Exide Life	0.566	1.121	0.566	0.474
9	Future Generali Life	0.288	0.387	0.288	0.165
10	HDFC Life	0	0	0	0
11	ICICI Prudential Life	0.125	0.161	0.152	0.144
12	IDBI Federal Life	1.449	0.957	0.592	0.043
13	India First Life	0	0	0	0
14	Kotak Mahindra Life	0	0	0	0
15	Max Life	0.117	0.013	0.11	0.016
16	PNB Met Life	0.62	0.073	0.383	0.208
17	Reliance Nippon Life	2.674	2052	0.728	0.495
18	SBI Life	0	0	0	0
19	Shriram Life	0.142	0	0.125	0
20	Star Union Dai-ichi Life	1.18	0.701	0.541	0.047
21	Tata AIA Life	0	0	0	0
22	LIC of India	0	0	0	0

Exhibit 7: Inefficiency readings using ShinyDEA app

We would therefore focus on input orientation, where the data is less ambiguous. The inefficiency readings using the input orientation option is as given in Exhibit 8. We have earlier mentioned in section 3.2 the advantages of the variable return to scale model or the BCC model. When we compare the BCC results with constant returns to scale or the CCR model, it is evident that the inefficiencies are lower (which means efficiencies are higher). This is primarily because the CCR model has a straight line efficiency frontier, whereas the BCC model has a convex line efficiency frontier, thus reducing the distance to the efficiency frontier for the identified inefficient DMUs. The difference in inefficiency, which is lower for BCC than the CCR model is because the scale inefficiency is ignored in the BCC model. The BCC model only focuses on the pure technical efficiency and not on the overall technical efficiency.

Sr No	DMU's	CCR Model Input	BCC Model Input
1	Aditya Birla Sun Life	0.497	0.462
2	**Aegon Life**	**0.311**	**0**
3	**Aviva Life**	**0.865**	**0.242**
4	Bajaj Allianz Life	0.425	0.231
5	Bharti Axa Life	0	0
6	DHFL Pramerica Life	0	0
7	Edelweiss Tokio Life	0	0
8	Exide Life	0.566	0.474
9	Future Generali Life	0.288	0.165
10	HDFC Life	0	0
11	ICICI Prudential Life	0.152	0.144
12	**IDBI Federal Life**	**0.592**	**0.043**
13	India First Life	0	0
14	Kotak Mahindra Life	0	0
15	**Max Life**	**0.11**	**0.016**
16	PNB Met Life	0.383	0.208
17	Reliance Nippon Life	0.728	0.495
18	SBI Life	0	0
19	**Shriram Life**	**0.125**	**0**
20	**Star Union Dai-ichi Life**	**0.541**	**0.047**
21	Tata AIA Life	0	0
22	LIC of India	0	0

Exhibit 8: Inefficiency readings using Input Orientation

In Exhibit 9, we have identified DMUs where the difference in inefficiency is over 50% between the CCR and BCC model inefficiency readings. It can be surmised that in case we would have followed the CCR model, then there would have been many incorrect deductions and incorrect benchmarks for improvement. To highlight this point, we have identified DMUs where the difference in inefficiency (CCR v/s BCC) is over 50% for further analysis. We will also highlight the targets for inefficiency reduction set by the CCR and the BCC models.

The inefficient DMUs considered for analysis are Aegon Life, Aviva Life, IDBI Federal Life, Max Life, Shriram Life and Star Union Daichi Life. In the case of other inefficient DMUs like Bajaj Allianz Life, the difference between CCR inefficiency readings and BCC inefficiency readings is less than 50% and hence, are not considered for further analysis. It is however established that the inefficiency readings of the BCC model are always less when compared with the inefficiency readings of the CCR model.

Sr No	DMU's	CCR Model Input	BCC Model Input	Is Difference >= 50%?
1	Aditya Birla Sun Life	0.497	0.462	No
2	**Aegon Life**	**0.311**	**0**	**100.00%**
3	**Aviva Life**	**0.865**	**0.242**	**72.02%**
4	Bajaj Allianz Life	0.425	0.231	No
5	Bharti Axa Life	0	0	
6	DHFL Pramerica Life	0	0	
7	Edelweiss Tokio Life	0	0	
8	Exide Life	0.566	0.474	No
9	Future Generali Life	0.288	0.165	No
10	HDFC Life	0	0	
11	ICICI Prudential Life	0.152	0.144	No
12	**IDBI Federal Life**	**0.592**	**0.043**	**92.74%**
13	India First Life	0	0	
14	Kotak Mahindra Life	0	0	
15	**Max Life**	**0.11**	**0.016**	**85.45%**
16	PNB Met Life	0.383	0.208	No
17	Reliance Nippon Life	0.728	0.495	No
18	SBI Life	0	0	
19	**Shriram Life**	**0.125**	**0**	**100.00%**
20	**Star Union Dai-ichi Life**	**0.541**	**0.047**	**91.31%**
21	Tata AIA Life	0	0	
22	LIC of India	0	0	

Exhibit 9: DMUs with differences in inefficiency readings of greater than 50%

The lambdas or the raw weights assigned to the peer units are shown in Exhibit 10a using the CCR model and in Exhibit 10b using the BCC model. The first observation here is that Aegon Life and Shriram Life which were shown as inefficient in the CCR model, are found to be efficient in the BCC model (inefficiency measure 0). Further, it will be seen that both Aegon Life and Shriram Life become the benchmark for inefficient DMUs. The lambdas are the shadow prices of the primal formulation which limits the efficiency to 1 (inefficiency to 0). The lambdas or shadow prices for benchmarking are shown in Exhibits 10a and 10b.

Sr No	DMU's	Lambda 5	Lambda 6	Lambda 7	Lambda 10	Lambda 13	Lambda 18
2	**Aegon Life**		0.31			0.12	
3	**Aviva Life**	0.03		0.02	0.01		
12	**IDBI Federal Life**	0.08			0.02	0.1	
15	**Max Life**				0.34	1.03	
19	**Shriram Life**	0.01				1.18	0.01
20	**Star Union Dai-ichi Life**	0.05				0.25	

Exhibit 10a: Lambdas for inefficient DMUs using the CCR Model

Sr No	DMU's	Lambda 2	Lambda 5	Lambda 7	Lambda 10	Lambda 13	Lambda 19
2	**Aegon Life**	1					
3	**Aviva Life**	0.75				0.25	
12	**IDBI Federal Life**	0.55				0.45	
15	**Max Life**				0.41	0.59	
19	**Shriram Life**						1
20	**Star Union Dai-ichi Life**	0.53		0.02		0.44	

Exhibit 10b: Lambdas for inefficient DMUs using the BCC Model

A second observation for the CCR model is that the inefficiency factor is more than 1, which has resulted in lambdas being more than 1. It is difficult to comprehend the reason for the same or make any use of this information. However, in the BCC model, the inefficiency is not more than 1 and consequently, the lambda values are less than one and collectively total to one. This model is therefore more suitable for benchmarking and for setting the improvement targets when the DMUs are different organizations, whereby the scale of operations is not similar. In short, when the DMUs are not homogeneous, the BCC model is more suitable. We next present the targets for the inefficient DMUs using the CCR and the BCC model in Exhibit 11.

DMU's	Direct Selling Agents @	No of Branches 2017 - 2018	Years in Busness	Claims settled in 30 days	Total Claims settled in full year
Input Target using CCR Model					
Aegon Life	4018	40	5	321	372
Aviva Life	2250	12	1	133	152
IDBI Federal Life	3998	26	2	414	477
Max Life	27906	171	17	5090	5853
Shriram Life	3328	44	12	1814	2110
Star Union Dai-ichi Life	1847	17	3	386	450
Input Target using BCC Model					
Aegon Life	**No inefficiency**				
Aviva Life	4719	70	11	746	804
IDBI Federal Life	3903	59	11	919	1023
Max Life	32569	187	14	5228	5998
Shriram Life	**No inefficiency**				
Star Union Dai-ichi Life	4393	60	10	897	1000

Exhibit 11: Targets on inputs for inefficient DMUs under the CCR and the BCC model

Aegon Life and Shriram Life would be having absurd targets using the CCR model, but in case of the BCC model, their existing targets are quite enough. This happens because the CCR model lists these two life insurers as inefficient, whereas the BCC model lists them as efficient. We should then consider the reasons therein and ponder on why BCC model is the best model for the present application. The next section presents a comparative analysis of the CCR and BCC models.

5.3 Comparative Analysis of the BCC and CCR model:

- The first observation is that the inefficiency measure by the BCC model is always lower than the CCR model. Why does this happen? This is because the BCC model allows for variable returns to scale. The convexity constraint ensures that the composite unit is of similar scale size as the unit being measured. The resulting efficiency in the BCC model is at least equal to or more than the efficiency measured by the CCR model. Accordingly, the inefficiency measured by the BCC model is lower or at most equal to the inefficiency measured by the CCR model. In the case of life insurers, the area of operations, the product offerings, commencement date of the business are all different, which effectively makes the scales of measurement different. Hence, the BCC model is better than the CCR model in this case and in all situations where the scale variation is a distinct possibility.
- The DEA techniques are useful for those DMUs which are homogeneous and in the same line of business. Although life insurers have similar businesses, their scale of operations, technology employed and focus of business vary. Accuracy of the technique employed would have been higher if we were comparing the technical efficiency of various branches of the same organization rather than different organizations. It should be remembered that the concept of DEA is Pareto optimality, which states that within the given limitations of resources and technology, there is no way of producing more of the desired commodity without replacing some other desired commodity.
- When the CCR model is used, the estimated efficiency score remains the same irrespective of whether there is input orientation or output orientation. We can see this clearly in Exhibit 7, where for all the life insurers with inefficiency less than 1, the inefficiency values remain the same irrespective of their orientation. In the constant returns to scale or the CCR model, the outputs would increase in the same rate as the increase in inputs, which is not factually correct.
- The BCC model measures the pure technical efficiency (PTE) whereas the CCR model measures the overall technical efficiency (OTE). For the IRDAI data listing many businesses, pure technical efficiency is better than the overall technical efficiency. There is another factor that must be noted, and that is, the OTE has two components, the PTE and the scale efficiency (SE). We might have situations where the firm is able to convert the

inputs into outputs efficiently, implying PTE is high, but would be OTE inefficient due to it being either too big or too small related to the optimum size. Therefore, inefficiency could be a result of inefficient operations or adverse conditions under which it operates. This is also the reason why the inefficiency score in the BCC model is less than the CCR model. Amongst the six DMUs selected for study, two DMUs namely Aegon Life and Shriram Life are efficient as per the BCC model and this is actually pure technical efficiency. The same DMUs are inefficient as per overall technical efficiency readings because they are scale inefficient. Aegon Life and Shriram Life are by far, the smallest in terms of operations and thus, the inefficiency under CCR is a result of size disadvantage or SE. Hence, the CCR model was not apt in this analysis.

- A thumb rule in DEA analysis is that the dataset should be at least 3 times the total sum of inputs and outputs. In our present study, we have 5 inputs and 4 outputs, necessitating minimum 27 DMUs. However, since we have only around 22 life insurers operating in India, the discretionary power of the model is reduced. In such scenarios, the quest therefore should be for pure technical efficiency, which is provided by the BCC model and not the CCR model.
- The scale efficiency is obtained by dividing the OTE (CCR model efficiency) by the PTE (BCC model efficiency). Exhibit 12 shows the scale efficiency for all the DMUs.

Sr No	DMU's	CCR Model Input	BCC Model Input	Scale Efficiency
1	Aditya Birla Sun Life	0.503	0.538	0.935
2	**Aegon Life**	0.689	1	0.689
3	**Aviva Life**	0.135	0.758	0.178
4	Bajaj Allianz Life	0.575	0.769	0.748
5	Bharti Axa Life	1	1	1
6	DHFL Pramerica Life	1	1	1
7	Edelweiss Tokio Life	1	1	1
8	Exide Life	0.434	0.526	0.825
9	Future Generali Life	0.712	0.835	0.853
10	HDFC Life	1	1	1
11	ICICI Prudential Life	0.848	0.856	0.991
12	**IDBI Federal Life**	0.408	0.957	0.426
13	India First Life	1	1	1
14	Kotak Mahindra Life	1	1	1
15	**Max Life**	0.89	0.984	0.904
16	PNB Met Life	0.617	0.792	0.779
17	Reliance Nippon Life	0.272	0.505	0.539
18	SBI Life	1	1	1
19	**Shriram Life**	0.875	1	0.875
20	**Star Union Dai-ichi Life**	0.459	0.953	0.482
21	Tata AIA Life	1	1	1
22	LIC of India	1	1	1

Exhibit 12: Scale Efficiency of DMUs

- In the BCC model where λ denotes the shadow price of efficient frontier DMUs. If we allow $\sum \lambda \leq 1$, we will have non-decreasing returns to scale and if we allow $\sum \lambda = 1$, we will have non-increasing returns to scale. The CCR model is unable to ensure that the inequalities of the type non-increasing or non-decreasing are avoided, as a result of which the shadow prices may or may not total to 1. As the BCC model calculates the pure technical efficiency net of scale effect, it captures the pure resources conversion efficiency irrespective of the increasing return to scale, or constant return to scale, or decreasing return to scale. This aspect is clearly observed in Exhibit 10a (where the total of λ is not equal to 1) and in Exhibit 10b (where the total of λ is equal to 1).

6 Findings: It is needless to say that the Data Envelopment Analysis (DEA) is a wonderful method for benchmarking and for computing the efficiency of DMUs. Some of the advantages of the DEA models include ease of handling multiple inputs and outputs having different units, not requiring any assumption of the functional form relating to inputs and outputs, and not requiring prior judgement on the relative importance of the inputs or outputs. Having said that, the models CCR and BCC can both be effective and ineffective under certain circumstances.

6.1 Situations where CCR model is applicable –

- DMUs should be homogeneous by which we mean part of the same organization without much variations in scale. In the example of NMIMS performance measurement of various divisions referred to in the introduction of this paper, all the divisions belong to NMIMS SBM and thus, were homogeneous to a large extent.
- The basic DEA approach using the CCR model is applied to the unitary evaluation of homogeneous units (rather than organizations). The requirement of homogeneity is fulfilled only by the units or branches of the same business unit in which case CCR can be applied.
- The overall technical efficiency (OTE) has the component pure technical efficiency (PTE) and the scale efficiency (SE). So, when the scales are dissimilar, CCR should not be applied.
- The CCR model assumes that there is perfect competition and we know that this is not true in practice. Imperfect competition, financial constraints, control steps and other factors can cause DMUs not to operate at their optimal size. It is therefore necessary to evaluate the DMUs for absence of the above listed factors to apply the basic CCR model. As explained earlier when we considered 10 divisions of the same B school, none of these constraints are present, thus allowing the application of the CCR model.

6.2 Situations where the BCC model is applicable –

v Whenever there is an excess influence of scale inefficiency, the BCC model is applicable. In case of the life insurer efficiency analysis, each business had different scales of operation necessitating focus only on pure technical efficiency (PTE), possible only in the BCC model.

v The BCC model can be assumed to be more realistic than the CCR model because it takes cognizance of the imperfections in practice like imperfect competition. So, if the researcher believes that the DMUs fall in the category of imperfect competition, then the BCC model becomes applicable.

v In general, when comparing the DMUs which are sectoral participants and not homogeneous, the BCC model is more applicable. We strongly recommend applying the BCC model for evaluating the efficiency of the public sector and private sector services businesses.

7. Conclusions:

The services sector is one of the important contributors to the GDP in an emerging economy like India. It is therefore, imperative that the efficiency measures for each of the service units be well thought out. In case the measurement of efficiency has a structural shortcoming, then the entire analysis could be rendered meaningless. Prominent considerations in application of the appropriate DEA technique would be the scale measurements, input or output orientation, temporal effects, variable or constant returns to scale and the number of DMUs vis-à-vis the inputs and outputs parameters.

In our analysis, we have found that when the DMUs are not homogeneous, it is better to use the BCC model which identifies the pure technical efficiency, ignoring the scale efficiency. We have considered different life insurance corporations and as a result, the scale of operations had a considerable variation. Most of them had all-India operations, but many had their pockets of influence more than the others. The government life insurance company LIC has the maximum number of branches and clientele due to the first mover advantage in this business. Hence, the input oriented variable returns to scale BCC model measuring the PTE was found suitable. In case we need to further analyse the branch efficiency of LIC or other life insurers within their network, then we can consider the CCR model.

8. Managerial Implications:

DEA needs no formal introduction and has been widely in use since Cooper, Charnes and Rhodes developed the basic model in 1978, developing the idea generated in the seminal work of Farell in 1957. The advantage of the DEA technique over the conventional regression-based production function approach is that it is a non-parametric technique that does not require a priori. It is also able to handle multiple input and output variables with different units. And this is also the source of problems. When no laid down application procedures are available, the researcher is free to choose any model as is convenient to implement. The researcher may also presume that the relativity of efficiency of DMUs is correct. Unless the inefficiency is further examined, the choice of DEA model can impair the correct analysis. The researcher should, amongst other things, pay attention to the percentage of homogeneity within the DMUs and if this is not very encouraging, switch to models like the BCC which can work with lesser homogeneous DMUs.

9. Applicability and Generalizability:

- Input or Output orientation remains the key in the DEA analysis. It is easy to set targets for attaining efficiencies, but whether the practical aspects of these targets are actually considered needs to be determined. We might set a target for life insurance policies sold, but the question is whether the externalities allow us the freedom to achieve these targets. Rather a target on inputs like number of branches could be better administered.
- The inefficiency ratings could at best be considered as an indicative rating, especially since the same is obtained by comparing the DMU with other DMUs. If the parameters of comparison are not entirely correct, then the inefficiency readings would be meaningless. For a life insurance company located in the eastern part of the country, the economic and geographical considerations would be different than of those located in the western part of the country. How can we then have a branch in the west set a benchmark on performance for a branch in the east? Nevertheless, without having any comparison with other similar branches, there is no method to rate the inefficiency. Window DEA techniques could perhaps be considered in these situations.

It could be advisable to use more than one DEA technique and analyse the reasons for the difference in the inefficiency scores of the techniques. Once the reasons are identified, it would help in identifying the real problem and thus reduce the error component in the analysis.

- The size of the data is an important factor and the thumb rule of DMUs equals to three times the total number of inputs and outputs should be followed for effectiveness of the DEA techniques.
- As mentioned earlier, in the literature, data authenticity is the key to the usefulness of the DEA technique. In our research paper, the data is obtained from the regulator's website and hence, authenticity is not an issue. For all DEA applications, the content validity remains the key feature for its successful application and use.

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***Pradeep Pai** received the Bachelor's degree in Production Engineering and Master's degree in Management from University of Mumbai in the year 1989 and 1991, respectively. After having worked in Industry and as a visiting faculty teaching Decision Sciences related subjects for over 28 years, he is now working as a Full time Associate Professor in Narsee Monjee Institute of Management Studies and Research, School of Business Management. He is currently pursuing his Ph.D. in Business Administration from Faculty of Management Studies, Aligarh Muslim University under the guidance of Dr. Bilal M Khan and Dr. P N Mukherjee. He can be reached at pradeep.pai@sbm.nmims.edu*

***T. Kachwala,** Professor, School of Business Management (NMIMS, Mumbai), is B.E. (Mechanical Engineering) from VJTI, MAM from NMIMS, and Ph.D. from North Gujarat University. He has published 3 Knowledge Management Series books, 3 Distance Learning books, 1 Case Study, (All NMIMS Publications), more than 20 research papers in refereed journals and conferences, and co-authored 2 Text Books. He has more than 27 years of teaching experience in Operations Management & Decision Science and 13 years of industry (factory) experience at Godrej Appliances Limited. He can be reached at t.kachwala@sbm.nmims.edu*