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Utilization of Intangibles Assets and the Performance of Public Sector Enterprises in India: DEA Analysis

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Abstract

Recent upsurges in intangible investment to boost Central Public Sector Enterprises' (CPSEs') capacity for production have raised a number of questions regarding the direction of decisions and the real management space that makes them a reality. A somber An alarming trend of crisis in the assessment and distribution of intangibles was shown by this study on the value of intangible expenditure and capitalization in enhancing future returns.Using the input-oriented Variable Returns to Scale (VRS) weighted measure-specific Data envelopment analysis (DEA) model with the R software, The contribution of the four inputs—software spending, other R&D expenditures, materials, and employee costs—to a set of productive activities that encompass revenue and net-value-added is critically examined in this study. These operations are more consistent in improving production capacity and profit.. The study is based on Nabaratna Enterprises' dataset from the last ten years. Using Data Envelopment Analysis (DEA), this study compares the technical and scale efficiency of the CCR Charnes–Cooper–Rhodes (CCR) and Banker–Charnes–Cooper (BCC) models to assess the effectiveness of Decision-Making Units (DMUs). While factors associated with creative activities, such R&D and software investment, could not duplicate the same discriminative power in alternative models, the baseline DEA model successfully differentiated between efficient and inefficient DMUs. Despite maintaining an average technical efficiency of about 70%, the BCC model in particular incorrectly categorized a larger percentage of DMUs as efficient, with the percentage of efficient units sharply increasing from 21.25% to 56–60%. The study also shows that scale efficiency had a greater impact on some units' efficiency than technical efficiency, including National Thermal Power Corporation Limited (NTPC), suggesting inefficiencies in management. Bharat Petroleum Corporation, on the other hand, could do better by expanding its business. Additionally, the data showed that R&D and software expenditures had a major effect on some units' efficiency, especially NTPC. With only 11% of units operating at best practice levels and a lack of consistency between DMUs, the study emphasizes the significance of size in efficiency scores. The multidimensional performances of the firms over the study period were not consistent, according to the results.

Keywords: R&D Spending, Measure-Specific Optimization and DEA Efficiency Ratings

Introduction

The study explores the business performance is affected by varies intangible spending, especially in R&D. R&D expenditure and financial results are positively correlated, according to recent studies. The accounting field highlights the importance of varied expenditure in fostering innovation and competitiveness, despite skepticism about it. Businesses gain more when innovations are broadly adopted (Areti & Kostas, 2017).

There has been much discussion in recent years about the diversity aspects of intangible spending and how it affects business performance. A number of trends were highlighted by the accounting field and findings. (Areti & Kostas, 2017);(Ferdaous &Marian, 2020). Notwithstanding the diverse trends of various intangible expenditure metrics that lead to disparate firm rankings (Jun-You, 2014);(Negin & Jafar, 2018); andIt is crucial for businesses to shatter the uncertainty and suspicion around varied intangible spending(Wang E. C., 2007); (Tuan & Nguyen, 2022). It appears reasonable to diversify R&D spending to some extent in order to withstand the intense competition, and the academic community will keep working in this area to replicate some of the salient characteristics of that business unit.

Following historical results (Jeongjin & Juneseuk, 2017);(Marios & Palitha, 2020);using a systematic process to transform a technology's potential into an R&D plan(Chinho & Cheng-Yu, 2012), It is found that Spending on R&D and its financial performance was proven to be positively correlated (Hyoungsuk & Hyungjun, 2020). A company that invests much in intangibles to create a new product or service makes more money if the invention is broadly adopted. (Pegah & Peter, 2018); (Tang & Jianping, 2021).

The aim of the study is to examine how intangible spending is distributed and diversified, especially in public sector organizations, while taking firm-specific factors like size, profitability, and corporate governance procedures into account. By studying the risks and rewards of various R&D expenditure patterns in emerging countries and comparing best practices from Navaratna businesses, the study intends to investigate how decision-making units (DMUs) might enhance managerial choices in intangible investments.

The crucial question is that how can the managerial decisions be improve in allocating intangibles investments and the direction and control of various decision variables with regard to best practise benchmarking . The argument put out in this study is that a decision-making unit (DMU) should take into account an element or set of elements as a decision value driver when a set of multiple performance measurements reveals that one or more aspects are important for upholding and reaching the best practise. Navaratna categorized enterprise. To consider the measure of specific company efficiency in each DMU, we define weighted measure-specific scores by taking into account the company sizes.

Literature Review:

- This study focus the findings of the critical evaluation of the evaluated literature that are more pertinent to the important issues and to provide answers to them, using the eligibility criteria for each dimension as a framework of includes. Research findings from various studies are organized and documented according to outcome measures in order to obtain a new viewpoint on the problems. Since their innovation systems are still in their infancy, many developing countries still lack the knowledge required to facilitate the creation of resources that can be used economically.(Sutz, 2000). Some aspects of intangibles increase productivity, while others do not, according to a study on banks' investments in intellectual capital to boost output.(Godfred & Pattanayak, 2019).
- In research and development decisions in the R&D investment model when analyzing firms' engagement in research as compared to development activities, it predicts higher spending in both activities for larger firms, but it also found that research intensity decline with firm size(Annette & Anwesha, 2022). It is found that agency costs experience therefore, agency expenses are reduced at both low and high business size and R&D activity levels. Firm size and R&D activity have a maximum value in this instance. (Giorgio & Stephen, 2022).
- This study is about corporate practices on intangible investments in enhancing productive capability, both in software expenditure (competitive profit efficiency) and other R&D spending (expansive productive efficiency) dimensions. The objective of this study is specifically focus on the diverse pattern of Software and other R&D spending on both enduring and expansion capabilities with the revenue, and net value added considering the various types of decision-making challenges that the Navaratna PSEs are now operational to improve and verify for uniformity in the spending pattern and productive performance ranking between the enterprises under study through the DEA-Sensitivity score. There are six variables our of which four variables are input namely material consumption, employee expenditure, spending on software, spending on other R&D and output varials are returns and net value added.
- The findings show that different businesses have different multifaceted financial performance and intangible expenditure efficiency. Efficiency is correlated with corporate size, particularly for companies such as ONGC, BHEL, and GALE, and larger enterprises with higher intangible spending may not always perform better than smaller ones.
- Taking into account the conceptual framework, the objective of the research, and the requirement to support the research question as emphasised above from the theoretical propositions the following hypothesis is considered:
- H0: With a set of multiple decision variables, there emerges no uniformity in the performance grades between the Navaratna Enterprises under study, and the Enterprises do not minimize the risk of diverse spending patterns on intangibles in achieving the best practice score with the changes in the value of sizes of the companies.
- HA: With a set of multiple decision variables, there emerges uniformity in the performance grades between the Navaratna Enterprises under study, and the Enterprises do minimize the risk of diverse spending patterns on intangibles while using the modifications to achieve the best practise score in the value of sizes of the companies.
- This analysis is consistent with previous research that uses firm-level data to examine how several intangible spending factors, including firm size, affect performance.

Theoretical Framework

- This research revolvs around exploring the different spending patterns affect intangible investments—more especially, software expenditure and other R&D spending—and how this affects Navaratna Public Sector Enterprises' (PSEs') performance and capacity for productivity. The purpose of the study is to ascertain whether spending trends are consistent and how they impact these businesses' performance and efficiency.
- Provides an overview of the general subject of intangible spending and how it relates to business performance. Highlight variety of accounting-related developments and discussions around intangible investments. Provides an overview of previous studies on intangible spending and how it affects corporate governance, innovation, R&D, and business success. Talks about how many factors affect R&D investment and corporate performance, as well as the role of intangibles in emerging economies.
- Describes the study's goals for examining software and R&D spending trends and how they affect the performance of Navaratna businesses. Draws attention to the need of researching these trends and how they affect corporate decision-making. Formulate research questions on how spending habits affect intangibles and how performance grades are consistent. Proposes hypotheses concerning the relationships between spending patterns, firm size, and achieving best practice scores.
- Describes the approach for data collection and analysis, focusing on input variables like material consumption, employee expenditure, software costs, and R&D spending. Outlines the DEA (Data Envelopment Analysis) methodology used to evaluate efficiency scores and categorize decision-making units.
- Presents the efficiency scores of Navaratna enterprises based on spending on software, R&D, and other factors. Discusses how different spending patterns influence efficiency and performance in these enterprises.

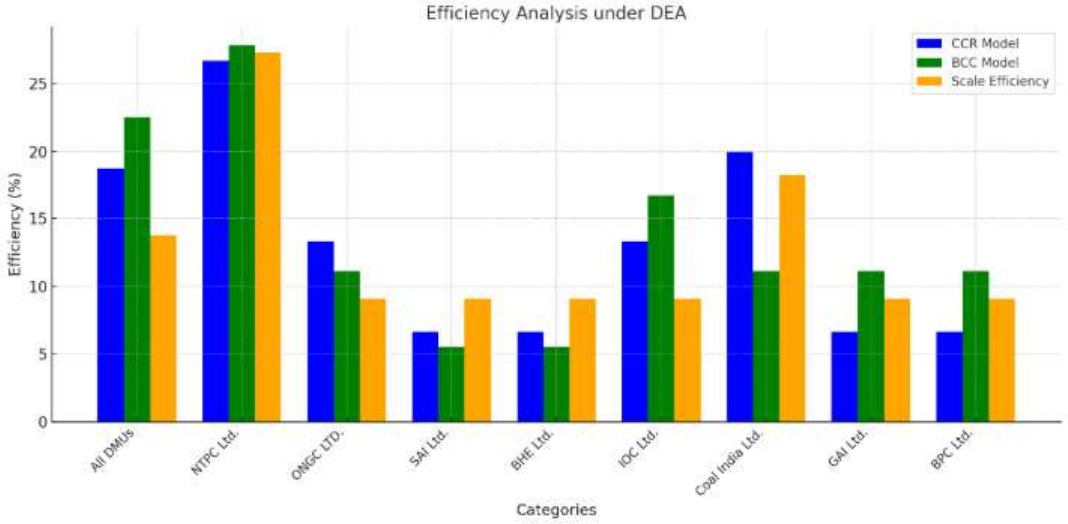

Fig:1 Trend of R&D spending in CRR, BCC Model and Scale Efficiency under Data envelopment analysis (DEA).

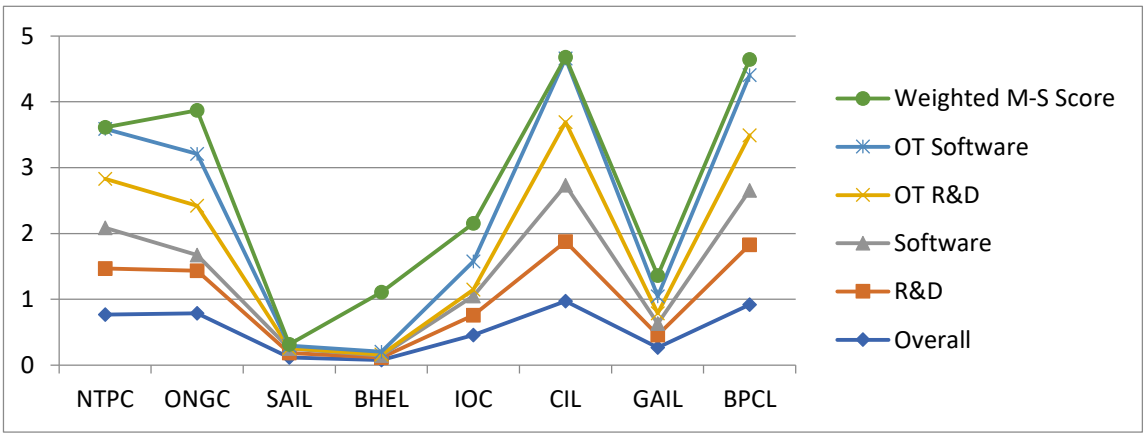

Fig:2 Efficiency Scores of NAVARATNA Enterprises under VRS.

Methodology:
Methodology refers to The methodical technique utilized to conduct research and gather relevant information in order to analysis test hypotheses or research questions. It involves selecting appropriate research methods, designing the study, collecting and analyzing data, and drawing conclusions based on the findings.

Research Design:

Research design is the overall plan or structure that guides the research process. The research design ensures that the study is conducted systematically and provides a framework for obtaining valid and reliable. This study framed an efficiency score by collecting secondary data (2013-14 to 2022-23).

Method:

Research method refers to the specific approach or technique used to analyze data in a research study. The presents research data are collecting from Public Enterprise Servey Report issued by the Department of Public Enterprise of Government of India.

Data Collection:

Research data collection involves to the relevant information or data to address research objectives. In this study all the data are secondary sources and collect from Public Enterprise Servey Report.

Data Analysis strategy:

Data analysis strategy is the planned approach for processing and interpreting collected data. It involves selecting appropriate statistical techniques or qualitative methods, organizing and cleaning the data, performing calculations or coding, and deriving meaningful insights or conclusions to address the research objectives or research questions. In this study, Data Envelopment Analysis (DEA), a non-parametric method is used to evaluate the relative efficiency of multiple decision-making units (DMUs). It compares the performance of DMUs that generate numerous outputs by consuming various inputs. DEA determines the efficiency scores by assessing how efficiently each DMU utilizes its inputs to generate outputs, allowing for benchmarking and identification of best practices with the help of R Studio-software is used for analysis the efficiency score.

Variables:

The contribution of the deciding factor from the container of four inputs—software spending, other R&D expenditures, materials, and employee—is examined in this study costsand returns for Navaratna Enterprises over the last 10 years, on a collection of profitable activities that include revenue and net value-added, since these are more consistent in increasing profit and production capacity when an input-oriented VRS is used., CCR, BCC and Scale efficiency weighted measure-specific DEA model with the R software,.

Research validation:

To determine the key variable, the best practice status based on the business units is categorized using the four input variables: material consumption, staff expenditure, software spending, and spending on other R&D. To determine whether a change in a key element's value significantly alters the performance grade between the units under examination, the efficiency score is analyzed. It then evaluated the score using the DMU size as an intervening variable from the unit's published data for the previous 10 years. For a specific inefficient model, the VRS measuresDMU_d,

$\theta_d^{k*}=\min\theta_d^k \quad d\epsilon N$
Subject to
$\sum_{j\epsilon E}\lambda_j^d x_{kj} = \theta_d^k x_{kd} k \epsilon \{1, ..., m\}$ (1)
$\sum_{j\epsilon E}\lambda_j^d x_{ij} \leq x_{id} i\neq k$
$\sum_{j\epsilon E}\lambda_j^d y_{rj} \geq y_{rd} r= 1,....., s \sum_{j\epsilon E}\lambda_j^d = 1$
$\lambda_j^d \geq 0, j\epsilon E,$

Where E indicates the index sets for the efficient and inefficient companies respectively and isidentified by the VRS envelopment DEA model. It determines the maximum potential decrease of input while keeping other inputs at the current level. We define weighted measure specific scores within each company by

considering the sizes of the companies with the net worth as a proxy of the size. We define kth input-specific benchmark-share for each efficient.DMU_j , j ϵ E,

$\lambda_j^k = \{\sum_{d \epsilon N} \lambda_j^{d*} (1- \theta_d^{k*}) x_{kd}\} / \{(1- \theta_d^{k*}) x_{kd}\}$

Where λ_j^{d*} and θ_d^{k*} are optimal values in (1) above.

.

Result:

The baseline DEA model demonstrated significance efficiency and strong discrimination amongst DMUs. Similar features could not be replicated by variables associated with inventive activity in another model. The CCR model's average efficiency went up a little. However, the BCC model did not adequately distinguish between efficient and inefficient units, misclassifying a larger percentage of DMUs as efficient. Interestingly, the BCC model's efficient unit percentage increase sharply from 21.25% in the base case to 56–60%.

Table 1 Results obtained Charnes–Cooper–Rhodes (CRR) model , Banker–Charnes–Cooper (BCC) Model and Scale Efficiency under Data envelopment analysis (DEA)

	CCR model		**BCC model**		**Scale efficiency**	
	Efficient DMU	**% total**	**Efficient DMU**	**% total**	**Efficient DMU**	**% total**
All DMUs	15	18.75	18	22.50	11	13.75
NTPC Ltd.	4	26.67	5	27.78	3	27.27
ONGC LTD.	2	13.33	2	11.11	1	9.09
SAI Ltd.	1	6.67	1	5.56	1	9.09
BHE Ltd.	1	6.67	1	5.56	1	9.09
IOC Ltd.	2	13.33	3	16.67	1	9.09
Coal India Ltd.	3	20.00	2	11.11	2	18.18
GAI Ltd.	1	6.67	2	11.11	1	9.09
BPC Ltd.	1	6.67	2	11.11	1	9.09
Average efficiency (%)	69.56		73.91		94.33	
Standard deviation	17.71		17.93		8.28	

The efficiency metrics for our basic DEA model are showing in Table 1.The CCR and BCC models consistent maintainingan average technical efficiency of about 70%. However, scale efficiency increases to greater degrees. The efficiency percentage for all units varies between 13.75% and 21.25%, depending on whether the model is BCC or CCR. It's interesting to note that NTPC Limited's scale efficiency exceeds its technical efficiency, indicating that inefficiencies stem from management and/or operations. However, Bharat Petroleum Corporation Limited's efficiency might be further increased by growing its operations. The DEA model results do not establish a significant performancesamong the enterprises are not uniform. Hence null hypothesis is rejected.

Table 2 Annexure-I Efficiency Scores of Navaratna Enterprises

As the drive is to identify the contribution of operating expenditure, spending on software, and other R&D investments to the performance grade, we selected a bundle of two variables namely revenueand net-value-added as the DEA outputs. A weighted measure specific VRS oriented efficiency scores of the operating unit depicts that only 11 percent of the total units are running at the best practice level and that efficiency may be highly correlated with size in these DMUs, otherwise there is no uniformity in the performance grades between the decision-making units under study. The input-oriented VRS efficiency scores' outcomes for NTPC exhibit that at least fifty percentof sceneries software and spending on R&D are the decisive value drivers. It appears that when other than R&D and software spending applied to each input measure separately, the input had no effect on the unit's efficiency classification because each related input may have been inefficient when other inputs were fixed at their current level.

It appears that when R&D and Software are applied for each input measure at a time, the R&D and Software expenditure input independently attained the efficiency classification in the last year of ONGC but the size-specific comparative efficiency score is optimal at the beginning and the fifth year of the study period. SAIL which is an inefficient unit, the optimal values are far from the best-practice frontiers, and it points out that spending on intangibles is not the decisive determinant in achieving the performance frontier. BHEL has the optimal solutions when the sizes of the unitsareconsidered to characterize the efficiency. Similarly, IOC depicts an optimal solution during the last two years of the study period but when the sizemeasureisinto consideration it attained the optimal score in the initial year of the study period.CI is efficient under the envelopment model in almost all the years during the study period but size-specific scores yield different efficient targets so the unit cannot be considered as efficient since both measure-specific and envelopment models produce the same frontier, a DMU is efficient under envelopment models if and only if it is efficient under measure-specific models.

GAIL with an untenable average score of 0.26528 indicates possible inefficiency exists in each associated input when other inputs are prearranged, the VRS scores are scattered throughout the study period. When R&D and Software spendingis exclusively applied for BPCit reaches the optimal solutions with a best-practice scoreduring the first half of the study period. However, when the sizes of the units are specifically considered the model yieldeddifferent efficient targets indicating the possible inefficiency of the DMUs

Discussion:

The DEA model effectively identified which DMUs performed better than others by demonstrating significant efficiency and good discrimination among them. These features, however, could not be reproduced when creative variables (including R&D and software spending) were included to a different model, indicating that not all variables have an equal impact on performance metrics. In the CCR model maintained an average technical efficiency of almost 70%, indicating a minor improvement in efficiency. On the other hand, the BCC model struggled to differentiate between units that were efficient and those that weren't. Its efficient unit percentage increased radically from 21.25% in the base case to 56-60%, and it incorrectly identified a sizable portion of DMUs as efficient (up to 60%). This change implies that the BCC model can miss more subtle differences in unit performance even though it is superior for scale efficiency. Technical efficiency constant across all models (about 70%), while scale efficiency varied more, with units showing efficiency percentages ranging from 13.75% to 21.25% depending on the model (BCC or CCR).

In this model, NTPC Limited's inefficiencies resulted from management and operations rather than technical performance because scale efficiency outperformed technical efficiency. As Bharat Petroleum Corporation notes that scale can occasionally trump management in influencing performance, it could increase efficiency by growing its activities. This study examined how R&D investments, software expenditures, and operations expenses affected performance. Notably, NTPC's R&D and software expenditures had a considerable impact on its efficiency scores; however, other inputs had no discernible impact on efficiency classifications when only one input was changed at a time. This implies that NTPC's success was significantly influenced by R&D and software investments. Different efficiency results were displayed by different units, such as SAIL and BHEL. BHEL outperformed SAIL in terms of unit size, although SAIL continued to be inefficient and far from the frontier of best practices. Similarly, IOC demonstrated size-based variability earlier in the trial period but functioned ideally over the last two years.

According to the investigation, efficiency was largely determined by size-specific performance, or the DMU's size. Certain units, such as CI and GAIL, showed effectiveness under envelope models but were unable to sustain steady performance when size was taken into account. According to the results, the multidimensional financial performances of the enterprises varied over the course of the study, and the efficiency of a small number of companies, such as ONGC, BHEL, and GALE, is strongly correlated with their size. Additionally, DMUs that spend more on intangibles do not necessarily perform better in terms of returns and net value added.

Conclusion:

In the DEA model's application effectively revealed performance variations across Decision-Making Units (DMUs), emphasizing their effectiveness and offering robust discrimination. R&D and software spending are examples of creative factors that were added to the model, but the results were inconsistent, indicating that they may not always have an impact on performance indicators. While the BCC model struggled to differentiate between efficient and inefficient units, particularly as its efficiency percentage for units increased sharply, misclassifying a significant number of DMUs as efficient, the CCR model maintained a steady technical efficiency of roughly 70%. This suggests that although the BCC approach would be more appropriate for evaluating scale efficiency, it might miss more subtle performance differences.

The findings show that scale efficiency outperformed technical efficiency and that operational and management issues were more responsible for inefficiencies in units like NTPC. The study also emphasized how crucial R&D and software spending are to increasing productivity, especially for NTPC, whose higher performance was largely due to these expenditures. The investigation also showed that larger units frequently performed better and that efficiency is frequently connected with unit size, as seen by the differing findings for several DMUs, including BHEL, SAIL, and IOC. However, since not all units benefited equally from such expenditures, the theory that increased spending on intangibles like R&D would result in better performance was disproved.

Limitation & Further study

The study is solely based on secondary data and it would have been different had it been able to incorporate the existing practices of their intangible spending decisions. The study has a scope to further research to extend the present research area by extending the sample size by incorporating Maharatna and Miniratna companies of the public sector enterprises. Studies can be made in this research area with a more extended study period. A comparative study can also be made with the tenure of the companies.

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