

**EFFICIENCY ANALYSIS OF INDIAN HIGHER EDUCATION INSTITUTIONS
USING NON-DISCRETIONARY AND ENVIRONMENTAL FACTORS**

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Abstract

Efficiency assessment in higher education often assumes homogeneous operating conditions; however, institutional age, governance structures, and regional environments significantly influence the conversion of inputs into outcomes. Failing to consider these contextual factors may lead to biased efficiency estimates, as they may attribute structural advantages to managerial performance. This study develops a contextualized efficiency framework for Indian higher education institutions using panel data from 76 institutions from 2020 to 2024. The analysis employs input-oriented CCR and BCC Data Envelopment Analysis (DEA) models to estimate baseline efficiency, followed by adjustments incorporating institutional age as a non-discretionary factor and environmental constraints based on governance type and geographic region.

The approach enables decomposition of efficiency into scale, age-related, environmental, and pure technical components. A Tobit regression model employed to investigate the impact of governance and regional characteristics on adjusted efficiency scores. The results reveal a consistent increase in efficiency estimates after accounting for contextual factors. Governance structures and regional conditions significantly explain variations in institutional performance. The study offers a context-sensitive framework for more reliable and equitable evaluation of efficiency in higher education.

Keywords: Data Envelopment Analysis; Non-discretionary inputs; Environmental efficiency; Tobit regression; Technical efficiency

Subject Classification: 90C05, 90C90

1. Introduction

Efficiency analysis has gained prominence in higher education due to increasing resource constraints, enrolment, and greater emphasis on accountability. Institutions expected to demonstrate effective utilisation of financial, human, and infrastructural resources while maintaining academic outputs. These pressures have led to wider adoption of quantitative performance evaluation techniques, particularly non-parametric methods. Data Envelopment Analysis (DEA) is widely used for evaluating relative efficiency when multiple inputs and outputs are involved. Its flexibility makes it suitable for higher education, where outputs are multidimensional and not easily aggregated. However, standard DEA models implicitly assume

that all decision-making units operate under similar conditions. This assumption is problematic in systems characterised by institutional heterogeneity.

Higher education institutions in India vary significantly in terms of institutional age, governance structures, and geographic context. Older institutions benefit from accumulated academic capital and established organisational structures, while newer institutions face adjustment costs. Governance regimes differ in autonomy, funding mechanisms, and regulatory flexibility. Regional conditions influence access to faculty, infrastructure, and external research opportunities. These factors lie largely beyond managerial control yet exert a direct influence on observed performance. Ignoring such contextual differences can lead to biased efficiency estimates, wrongly attributing structural advantages to managerial performance. While the DEA literature has proposed methodological extensions that include non-discretionary and environmental variables, empirical studies that simultaneously consider institutional age, governance type, and regional location are still limited, especially in the Indian context.

This study builds on the BCC framework by treating institutional age as a non-discretionary input and by adjusting for governance type and geographic zone. These refinements allow overall technical efficiency to be broken down into scale efficiency, age-related efficiency, environment-adjusted efficiency, and pure technical efficiency. To explore the role of context, Tobit regression employed to examine how governance and regional factors influence environment-adjusted efficiency scores. The aim is to provide an efficiency assessment that is both statistically robust and sensitive to the diverse realities of higher education systems. To achieve its objective, the study addresses three core research questions:

- **RQ1:** How does institutional age, when treated as a non-discretionary input, influence efficiency scores across Indian HEIs?
- **RQ2:** In what ways do governance type and geographic zone contribute to variations in efficiency over time?
- **RQ3:** How do scale-adjusted, age-adjusted, and environment-adjusted components contribute to overall technical efficiency?

2. Literature Review

Data Envelopment Analysis (DEA) is a non-parametric technique designed to evaluate the relative efficiency of decision-making units operating under multiple inputs and outputs. The original formulation assumes constant returns to scale, while subsequent extensions allow for variable returns to scale, enabling decomposition of overall efficiency into pure technical and scale components (Charnes et al., 1978; Banker et al., 1984). These models form the methodological foundation of most applied efficiency studies.

Early applications of DEA in the higher education sector focused on benchmarking universities and academic departments using simplified production structures. While these studies demonstrated the suitability of DEA for evaluating educational performance, they often assumed institutional homogeneity, thereby limiting the interpretability of efficiency scores in

heterogeneous systems (Johnes, 1996; Abbott & Doucouliagos, 2009; Worthington & Lee, 2008). In such contexts, measured inefficiency may reflect structural advantages rather than managerial performance.

Subsequent methodological developments addressed these limitations by incorporating non-discretionary and environmental variables into DEA frameworks. Approaches that allowed categorical and exogenous factors to influence efficiency measurement without distorting the production frontier improved the realism of efficiency assessment (Banker & Morey, 1986). Further refinements introduced slack-based measures that explicitly account for input excesses and output shortfalls, thereby enhancing discrimination among efficient units (Tone, 2001). Empirical evidence suggests that ignoring environmental effects and statistical noise leads to biased efficiency estimates, particularly in public sector applications (Fried et al., 2002).

The incorporation of contextual variables has therefore become a central theme in applied DEA research. Productivity and efficiency indices are sensitive to environmental constraints, reinforcing the need for context-aware modelling (Pastor & Lovell, 2005; Färe et al., 2004). Comprehensive methodological treatments further consolidated these advances by formalising extensions involving categorical variables, sensitivity analysis, and environmental adjustments (Cooper et al., 2007).

Within the higher education sector, institutional efficiency is shaped by multiple contextual factors, including governance frameworks, funding models, and institutional missions. Comparative studies across countries indicate that variations in governance arrangements contribute to systematic differences in efficiency outcomes, while institutional structures and strategic priorities play a significant role in determining performance (Agasisti & Pérez-Esparrells, 2010; Kuah & Wong, 2011). Recent efficiency analyses that incorporate sustainability and risk-related dimensions further demonstrate the increasing importance of external environmental constraints in influencing higher education performance (Dumitrescu et al., 2020; Olariu & Brad, 2022).

A significant strand of the literature employs multi-stage DEA approaches, in which first-stage efficiency scores are regressed on contextual variables in a second stage. Comparative evaluations of alternative second-stage specifications indicate that modelling choices can substantially influence inferences about environmental effects (Hoff, 2007; Johnson & Kuosmanen, 2012). Tobit regression remains widely used due to the censored nature of DEA efficiency scores and its interpretability in applied settings, despite the availability of bootstrap-based alternatives (Afonso & Aubyn, 2005; McDonald, 2009; Simar & Wilson, 2007).

In the Indian higher education context, Data Envelopment Analysis (DEA) has been widely employed to assess institutional efficiency, predominantly through traditional input–output-based models. Initial studies established the applicability of DEA for evaluating Indian educational institutions (Ramanathan, 2003). Subsequent research identified significant variations in efficiency levels among management institutions and universities; however, many of these studies did not adequately account for institutional heterogeneity and contextual differences (Debnath & Shankar, 2009; Tyagi et al., 2009). Recent investigations have further

explored efficiency variations across public universities and specialised institutions, yet key structural factors, including institutional age, governance framework, and regional context, remain insufficiently examined (Kaur, 2021; Ranjan & Singh, 2020).

Evidence from related sectors underscores the importance of contextual modelling in efficiency analysis. Studies in the Indian banking sector consistently incorporate ownership, scale, and regional effects within DEA frameworks, demonstrating that environmental factors explain a substantial proportion of observed efficiency variation (Saha & Ravisankar, 2000; Kumar & Gulati, 2010). Similar findings emerge from evaluations of entrepreneurial and research-oriented institutions, where structural characteristics are shown to influence performance outcomes more strongly than operational inefficiency alone (Loganathan & Subrahmanya, 2023; Maral, 2023).

International research increasingly applies advanced DEA models that incorporate categorical and environmental variables to assess university efficiency. Departmental-level analyses and institution-wide studies across different national contexts indicate that efficiency estimates become more robust and policy-relevant when contextual heterogeneity is explicitly modelled (Arcelus & Coleman, 1997; Shi et al., 2022). Studies focusing on research universities further confirm that scale effects, funding structures, and institutional maturity significantly influence efficiency outcomes (Dogan, 2023; Almeida et al., 2025).

Despite these methodological and empirical advances, limited attention has been given to the joint modelling of institutional age, governance structure, and geographic location within a unified DEA framework, particularly in the Indian higher education system. Most studies examine these factors separately or only add them after efficiency scores are calculated, which often leaves us with a fragmented understanding of why inefficiencies occur.

The present study addresses this gap by integrating institutional age, governance structure, and geographic location as non-discretionary variables within an extended BCC framework. By breaking overall efficiency into technical, scale, and environmental parts, and using Tobit analysis, this study connects with current DEA work while giving a more context-aware view of efficiency in higher education.

3. Methodology

3.1 Data and Variables

The study analyses a panel dataset comprising 76 higher education institutions observed during the period 2020–2024, with each institution considered as a decision-making unit (DMU). The selected input and output variables are modelled as discretionary factors, whereas institutional age is incorporated as a non-discretionary input to capture maturity-related effects. Governance structure and geographic zone are considered as environmental variables to account for contextual influences on institutional performance. The assumption of isotonicity between discretionary inputs and outputs is validated using Spearman's rank correlation analysis.

Table 3.1.1: INPUT-OUTPUT VARIABLES

Category	Variable Name	Type	Description / Measurement
Input Variables	Student Strength (SS)	Discretionary Input	Total student enrolment represents institutional scale.
	Faculty Quality and Experience (FOQ)	Discretionary Input	Composite measures capturing faculty qualifications, experience, and academic engagement.
	Financial Resources and Utilization (FRU)	Discretionary Input	Reflects the financial allocation and effectiveness of resource utilization.
Output Variables	Research Output (RO)	Discretionary Output	Composite indicators include Quality of Publications (QP), Intellectual Property Rights (IPR), and Footprint of Projects and Professional Practice (FPPP).
	Graduation Outcome (GO)	Discretionary Output	Represents student academic success and progression, including graduation and placement outcomes.
	Perception Score (PS)	Discretionary Output	Reflects institutional reputation and stakeholder perception as per NIRF rankings.
Non-Discretionary Variable	Institutional Age	Non-Discretionary Input	Number of years since attaining current institutional status (e.g., Central, Deemed, or State University), indicating maturity and legacy.
Environmental Variables	Zone	Environmental Variable	Categorical variables representing geographical regions include East, West, North, South, and Central, capturing spatial and administrative diversity.
	Governance Type	Environmental Variable	Categorical variable denoting institutional control: Centrally Funded (CFI), State Funded (SFI), or Privately Managed (PMI).

3.2 DEA Models

Input-oriented CCR and BCC models are first estimated to obtain baseline efficiency scores under constant and variable returns to scale. Institutional age is incorporated as a non-discretionary input within an extended BCC framework. Environmental adjustments are introduced by estimating separate frontiers for governance-homogeneous and region-homogeneous groups. A composite environmental efficiency score is calculated as the average of governance-based and zone-based efficiencies.

3.2.1 Input -Oriented CCR model (CRS)

For a DMU_h, the CCR efficiency score is obtained by solving :

$$\begin{aligned}
 & \text{Minimize: } \theta \\
 & \text{Subjected to :} \\
 & \sum_{j=1}^n \lambda_j x_{ij} \leq \theta x_{ih} ; \forall i \\
 & \sum_{j=1}^n \lambda_j y_{oj} \geq y_{oh} ; \forall o \\
 & \lambda_j \geq 0 ; \forall j
 \end{aligned}$$

Where $0 < \theta \leq 1$ indicates technical efficiency under constant return to scale (CRS)

3.2.2 Input-Oriented BCC Model (VRS)

Introducing the convexity constraints $\sum_{j=1}^n \lambda_j = 1$ gives the BCC model:

$$\begin{aligned}
 & \text{Minimize: } \theta \\
 & \text{Subjected to :} \\
 & \sum_{j=1}^n \lambda_j x_{ij} \leq \theta x_{ih} ; \forall i \\
 & \sum_{j=1}^n \lambda_j y_{oj} \geq y_{oh} ; \forall o \\
 & \sum_{j=1}^n \lambda_j = 1 ; \lambda_j \geq 0 ; \forall j
 \end{aligned}$$

3.2.3 Extended BCC with Non-Discretionary Input (EBCCA)

Institutional age(z_{aj}) is introduced as a non-discretionary input, acknowledging that legacy and maturity influence performance.

$$\begin{aligned}
 & \text{Minimize: } \theta^A \\
 & \text{Subjected to :}
 \end{aligned}$$

$$\begin{aligned} \sum_{j=1}^n \lambda_j x_{ij} &\leq \theta x_{ih}; \forall i \\ \sum_{j=1}^n \lambda_j y_{oj} &\geq y_{oh}; \forall o \\ \sum_{j=1}^n \lambda_j z_{aj} &\leq z_{ah} \\ \sum_{j=1}^n \lambda_j &= 1; \lambda_j \geq 0; \forall j \end{aligned}$$

3.2.4 Extended BCC with Environmental Variable (EBCCE)

The EBCCE model combines governance-based (EBCCG) and zone-based (EBCCZ) adjustments, while retaining age as a non-discretionary variable.

- **EBCCG:** Evaluates efficiency within governance-homogeneous groups (CFIs, SFIs, PMIs).
- **EBCCZ:** Assesses efficiency within regional cohorts (East, West, North, South, Central).

The composite environmental efficiency is calculated as: $EBCCE = (EBCCG + EBCCZ) / 2$

3.2.4.1 Extended BCC with Governance-Based Environmental Variable (EBCCG)

This model evaluates efficiency within governance-homogeneous groups: Centrally Funded Institutions (CFIs), State Funded Institutions (SFIs), and Privately Managed Institutions (PMIs).

Minimize: θ^G
Subjected to :

$$\begin{aligned} \sum_{j \in G} \lambda_j x_{ij} &\leq \theta^G x_{ih}; \forall i \\ \sum_{j \in G} \lambda_j y_{oj} &\geq y_{oh}; \forall o \\ \sum_{j \in G} \lambda_j z_{aj} &\geq z_{ah} \\ \sum_{j=1}^n \lambda_j &= 1; \lambda_j \geq 0; \forall j \in G \end{aligned}$$

3.2.4.2 Extended BCC with Zone-Based Environmental Variable (EBCCZ)

This model evaluates efficiency within Zone-homogeneous groups: East, West, North, South, and Central.

Minimize: θ^Z
Subjected to :

$$\begin{aligned} \sum_{j \in Z} \lambda_j x_{ij} &\leq \theta^Z x_{ij} ; \forall i \\ \sum_{j \in Z} \lambda_j y_{oj} &\geq y_{oh} ; \forall o \\ \sum_{j \in Z} \lambda_j z_{aj} &\geq z_{ah} \\ \sum_{j=1}^n \lambda_j &= 1; \lambda_j \geq 0; \forall j \in Z \end{aligned}$$

3.3 Efficiency Decomposition

Overall technical efficiency is decomposed into scale efficiency, age efficiency, environmental efficiency, and pure technical efficiency. This decomposition helps identify the sources of inefficiency across institutions.

$$\theta_{CCR} = \left(\frac{\theta_{CCR}}{\theta_{BCC}} \right) \times \left(\frac{\theta_{BCC}}{\theta_{EBCCA}} \right) \times \left(\frac{\theta_{EBCCA}}{\theta_{EBCCE}} \right) \times \theta_{EBCCE}$$

Where:

- $\frac{\theta_{CCR}}{\theta_{BCC}}$ = Scale Efficiency (SE)
- $\frac{\theta_{BCC}}{\theta_{EBCCA}}$ = Age Efficiency (AE)
- $\frac{\theta_{EBCCA}}{\theta_{EBCCE}}$ = Environmental Efficiency (EE)
- θ_{EBCCE} = Pure Technical Efficiency (PTE)

Thus, overall efficiency can be expressed as:

CCR Efficiency = Scale Efficiency × Age Efficiency × Environmental Efficiency × Pure Technical Efficiency

This decomposition enables researchers and policymakers to identify the sources of inefficiency—whether arising from scale limitations, contextual disadvantages, or managerial practices.

3.4 Tobit Regression

Environment-adjusted efficiency scores lie in the interval [0,1]. A Tobit regression model is therefore employed to examine the influence of governance type and geographic zone. Parameters were estimated using maximum likelihood, and Wald statistics were employed for inference.

Environmental efficiency scores θ_{EBCCCE} lie in the interval $(0,1]$. Thus, a censored regression is appropriate.

Let: θ_{ht} = efficiency of institution h in year t

Gov_{ht} = governance dummy variables (SFI, CFI, baseline = PMI)

$Zone_{ht}$ = Zone dummies (East, West, North, South, baseline = Central)

The latent model is.

$$\theta_{ht}^* = \beta_0 + \beta_1^T Gov_{ht} + \beta_2^T Zone_{ht} + \varepsilon_{ht} \quad \varepsilon_{ht} \sim Normal(0, 2\sigma^2)$$

Observed dependent variable:

$$\theta_{ht} = \begin{cases} 0, & \theta_{ht}^* \leq 0 \\ \theta_{ht}^*, & 0 < \theta_{ht}^* < 1 \\ 1, & \theta_{ht}^* \geq 1 \end{cases}$$

This estimation approach provides a robust foundation for evaluating efficiency differences across institutions.

4. Empirical analysis

RQ1: Institutional Age and Efficiency

The first research question (RQ1) investigates whether institutional age—treated as a non-discretionary input—has a measurable influence on institutional efficiency.

Table 4.1: Mean Differences Between BCC and EBCCA Efficiency Scores (2020–2024)

Year	Mean BCC	Mean EFFA	Mean Difference	Interpretation
2020	0.9279	0.941	0.0131	Scores increasing slightly when age is fixed
2021	0.9331	0.945	0.0120	Younger institutions lose relative advantage.
2022	0.9337	0.944	0.0107	Age-adjusted efficiency is consistently lower.
2023	0.9123	0.927	0.0145	Strongest upward shift in 2023
2024	0.9065	0.922	0.0159	Largest maturity effect in the final year

Table 4.1 shows that the mean differences between BCC and EBCCA scores are positive across all years, with the increase ranging $[0.0107, 0.0159]$. This pattern demonstrates that institutions' maturity tends to score higher unadjusted BCC efficiency scores, and the EBCCA model

corrects this upward bias by accounting for age-related advantages. To evaluate whether institutional age influences efficiency,

RQ2: Governance and Geographic Zone Effects

To address RQ2, a two-stage DEA framework was employed, in which environment-adjusted efficiency scores (EBCCE) were regressed on governance and geographic-zone variables.

Table 4.2. Tobit Regression of Efficiency (EBCCE) on Governance and Zone (2020–2024)

Year	Significant Governance	of	Significance of Zone Effects	Wald χ^2 (p-value)
2020	SFI , p=0.0407 *		None	10.33 (p=0.111)
2021	SFI , p=0.0166 *		South, p=0.063	16.27 (p=0.012) **
2022	CFI , p=0.031*		None	11.72 (p=0.069)
2023	None		None	12.15 (p=0.059)
2024	None		North, p=0.048*, East, p=0.003**, West, p=0.029 *	15.45 (p=0.017) **

Note: *p < 0.05, **p < 0.01

The Tobit regression results in Table 4.2 indicate that governance type and regional context shape institutional efficiency over time, with centrally funded institutions gaining an advantage by 2022. In 2023, these effects were minimal, suggesting a temporary convergence. By 2024, however, regional differences became visible again. Institutions in the north, east, and west began to lag behind those in the south, indicating a gradual widening of the performance gap. Taken together, governance and geography account for a small yet meaningful portion of the efficiency differences observed over the study period.

Table 4.3 Mean Environment-Adjusted Efficiency (EBCCE) by Governance

Governance Type	N	Minimum	Maximum	Mean (SD)
CFI	34	0.9200	1.0000	0.9831 (0.0215)
SFI	20	0.9300	1.0000	0.9854 (0.0215)
PMI	22	0.8900	1.0000	0.9593 (0.0357)

Table 4.3 shows that all governance types maintain high efficiency, with averages above 0.95. State-funded institutions perform the best, closely followed by centrally funded ones, while

private institutions lag slightly. The small gaps suggest broad convergence, though the wider spread among private institutions points to uneven management and varying levels of maturity.

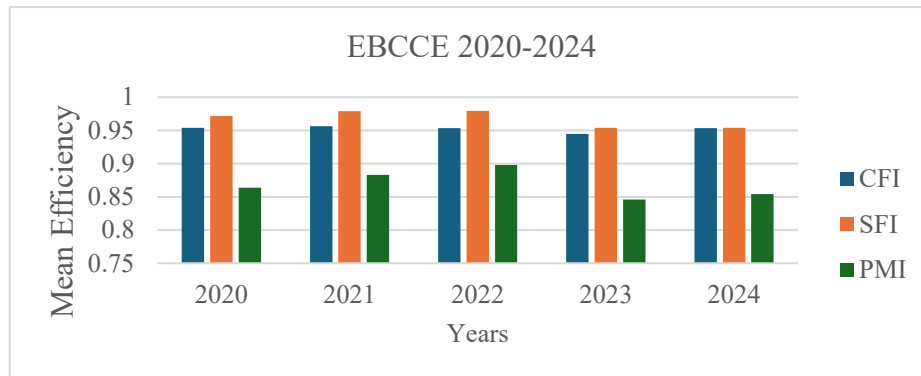


Figure 4.1: Mean of EBCCE across Governance

Figure 4.1 illustrates the mean EBCCE efficiency trends for 2020–2024. State-supported institutions consistently perform at a relatively prominent level compared to centrally funded institutions, which also show robust performance. In contrast, private institutions exhibit more fluctuation in efficiency scores and generally rank lower than both state and central institutions. Over time, the variance in mean scores across the three groups decreases, indicating that their performance levels are gradually converging.

RQ3: Decomposition of Efficiency Components

RQ3 examines the extent to which age-adjusted, environment-adjusted, and scale factors contribute to technical efficiency. By assessing these components separately, the impacts of institutional size, maturity, and geographic context can be identified. Recognizing sources of inefficiency provides a basis for targeted policy interventions that improve processes, reduce disparities, and support the sustainable development of institutions.

Table 4.4: Average Efficiency under different Environemnts

Efficiency Component	Description	Mean Efficiency Score	Standard Deviation
Scale Efficiency (SE)	Reflects operational size effects	0.94	0.05
Age Efficiency (AE)	Captures maturity-related effects	0.96	0.04
Environmental Efficiency (EE)	Captures zone & governance influences	0.92	0.06
Pure Technical Efficiency (PTE)	Reflects managerial/operational efficiency	0.95	0.03

Table 4.4 illustrates that inefficiencies related to size, age, environment, and management exist across all Indian higher education institutions (HEIs). Most HEIs achieve positive scores in

terms of scale and maturity, reflecting sufficient size and adequate infrastructure. However, environmental efficiency is considerably lower than overall efficiency scores, highlighting the influence of governance systems and regional disparities.

Correlation analysis shows that Environmental Efficiency is most strongly linked to Overall Technical Efficiency ($r = 0.949$, $p < 0.01$), with weaker associations for Scale Efficiency ($r = 0.386$, $p < 0.01$) and Age Efficiency ($r = 0.252$, $p < 0.05$). The regression results confirm this pattern: environmental efficiency exerts the strongest effect ($\beta = 0.93$, $p < 0.01$), age efficiency has a modest effect ($\beta = 0.175$, $p < 0.01$), and scale efficiency is not statistically significant ($\beta = 0.011$, $p = 0.736$). Overall, efficiency differences among Indian HEIs are driven more by governance and regional context than by managerial or size-related factors.

5. Summary and Conclusions

The findings demonstrate that contextual factors significantly influence efficiency estimates in higher education institutions. Institutional age captures maturity-related advantages that may otherwise be misinterpreted as managerial effectiveness. Incorporating environmental adjustments further reveals persistent disparities associated with governance structures and regional conditions, which shape institutional performance beyond managerial control. Although most institutions operate close to efficient scales, comparatively lower environmental efficiency suggests that structural constraints continue to affect performance outcomes. These results emphasize the importance of integrating non-discretionary and contextual variables into efficiency measurement frameworks to ensure more accurate benchmarking.

This study develops a context-sensitive DEA framework that incorporates institutional age, governance characteristics, and geographic location into higher education efficiency evaluation. By decomposing technical efficiency into scale, age-related, environmental, and pure technical components, the framework provides a more robust approach for comparing heterogeneous institutions. The findings highlight the limitations of traditional DEA models when applied to diverse institutional settings and demonstrate the value of contextualised efficiency analysis. The proposed methodology can be extended to other public sector domains where organizational performance is influenced by both managerial practices and external environments.

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