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ORIGINAL

Using Stochastic Frontier Analysis Algorithms to Study Corporate Capital Structure Optimization and Risk Management: A State-Owned Enterprise Research Perspective

Uso de algoritmos de análisis de frontera estocástica para estudiar la optimización de la estructura de capital corporativa y la gestión de riesgos: una perspectiva de investigación desde las empresas estatales

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ABSTRACT

For any industries, the measuring of Capital Structure Optimization (CSO) and Risk Management (RM) are essential aspect to improve performance and sustainability. State owned enterprise provide considerable challenges to perform the CSO and RM because of its inherent complexities and unique attributes. Further there are too little attempts were made to measure those attributes. This work is an attempt to study the influence of CSO and RM over the performance of State-Owned Enterprise (SOE). Particularly this study focuses on industries such as energy, utilities, telecommunications, transportation, manufacturing, financial services, real estate, healthcare, technology, and agriculture. The work study had employed a Translog Stochastic Frontier (TSF) model with Return on Assets (ROA) as the dependent variable and key financial ratios as independent variables. Using the data that was collected three years during the period from 2020 to 2023. The TSF model was optimized using goal programming approach based on set of constraints. The results from the findings have shown that the mean efficiency scores have improved across all industries after constraint applications.

Keywords: Capital Structure Optimization; Risk Management; State-Owned Enterprise; Machine Learning; Mean Efficiency.

RESUMEN

Para cualquier industria, la medición de la optimización de la estructura de capital (CSO) y la gestión de riesgos (RM) son aspectos esenciales para mejorar el rendimiento y la sostenibilidad. Las empresas estatales presentan desafíos considerables para realizar la CSO y la RM debido a sus complejidades inherentes y atributos únicos. Además, se han hecho muy pocos intentos para medir esos atributos. Este trabajo es un intento de estudiar la influencia de la CSO y la RM sobre el desempeño de las empresas estatales (SOE). En particular, este estudio se centra en industrias como la energía, los servicios públicos, las telecomunicaciones, el transporte, la fabricación, los servicios financieros, el sector inmobiliario, la atención médica, la tecnología y la agricultura. El estudio de trabajo había empleado un modelo de frontera estocástica translogarítmica (TSF) con el rendimiento de los activos (ROA) como variable dependiente y los índices financieros clave como variables independientes. Utilizando los datos que se recopilaron durante tres años durante el período de 2020 a 2023, el modelo TSF se optimizó utilizando un enfoque de programación de objetivos basado en un conjunto de restricciones. Los resultados de los hallazgos han demostrado que las puntuaciones de eficiencia media han mejorado en todas las industrias después de la aplicación de restricciones.

Palabras clave: Optimización de la Estructura de Capital; Gestión del Riesgo; Empresa Pública; Aprendizaje Automático; Eficiencia Media.

INTRODUCTION

The Capital Structure Optimization (CSO) and Risk Management (RM) are both considered as important factors of corporate finance. As those factors contribute in enhancing the financial performance and sustainability of State-Owned Enterprises (SOE).[1,2] The CSO of an enterprise includes a mix of debt and equity financing which directly impacts its capital cost, financial risk, and overall value.[3,4] So effective CSO is essential to for an enterprise to maintain an optimal balance between debt and equity.[5] Whereas the RM in an enterprise involves in identifying, assessing, and mitigating financial risks to protection the firm's financial health.[6,7] The SOW are considered as backbone of a nation's economy particularly of emerging and transitional economies.[8] Mainly the SOE engage in industries such as: energy, utilities, telecommunications, transportation, and manufacturing.[9] The financial efficiency of such SOE are of paramount importance as it directly impacts the corresponding nation's economy.[10,11] Some of the key areas of concern faced by SOE are CSO and RM as because it has to balance between commercial objectives and fulfilling social and public policy goals.[12] This challenge leads to inefficiencies, suboptimal financial structures, and heightened financial risks.[13]

For such a key factors of influence over SOE performance there was too limited attempts and study were focused using advanced analytical techniques to understand these factors.[14] The traditional models that were in practice to study these factors have limited ability to identify the complexities and unique attributes of SOE.[15,16] Stochastic Frontier Analysis (SFA) is an economic modelling method that are employed to ascertain the efficiency of an enterprise and are able to distinguish between random noise and inefficiency.[17] The SFA has the ability to find the key factors that influence the financial performance of SOEs by considering the variability and stochastic nature of financial data.[18] The works that had employed SFA for studying SOE-CSO and RM is too limited, which motivated to pursue this study. The proposed work attempts to employ the STA model in assessing the CSO and RM on SOE industries such as energy, utilities, telecommunications, transportation, manufacturing, financial services, real estate, healthcare, technology, and agriculture. For the data that was collected from these industries during a three year period from (2020-2023) the work exercised Translog Stochastic Frontier (TSF) model with each firm's overall financial performance as the dependent variable and factors such as Leverage Ratio (LR), Equity Ratio (ER), Return On Equity (RoE) as independent variables. Using the Maximum Likelihood Estimation (MLE) technique the work measures the efficiency and estimate the parameter.

METHOD

Data Collection

The data for this study was collected from SOE in China. The dataset spans the period from 2020 to 2023 and includes a variety of financial indicators. The following table presents the data type and the source of the data:

Table 1. Data types for each indicator

Indicator	Description	Source	Data Type
Debt Ratios	Total debt and total equity	SOEs' financial statements, Shanghai and Shenzhen Stock Exchanges	Numeric
Equity Ratios	Shareholders' equity and total assets	SOEs' financial statements, Shanghai and Shenzhen Stock Exchanges	Numeric
Profitability Metrics	Return on Assets (ROA), ROE	Bloomberg, Thomson Reuters Eikon	Percentage
Liquidity Ratios	Current ratios, quick ratios	SOEs' financial statements, Shanghai and Shenzhen Stock Exchanges, Bloomberg	Numeric
Risk Indicators	Beta values, default probabilities	Orbis, Thomson Reuters Eikon	Numeric/Probability
Operational Metrics	Asset turnover ratios, firm size (total assets, market cap)	Bloomberg, SOEs' financial statements	Numeric

As preprocessing the raw data was cleaned to remove any inaccuracies, such as typographical errors and inconsistencies in reporting formats. This involved cross-verifying reported figures against multiple sources and correcting any discrepancies. Missing data points were addressed using Mean Imputation Method (MIM). Outliers were identified and treated using winsorization. Normalization of the data was then performed to standardize the financial indicators by transforming the data to a common scale using Min-Max scaling. Also the dataset was segmented as shown in table 2 based on industry classifications to control for sector-specific effects.

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Table 2. Industry segmentation

Industry Classification	Description	Number of SOEs	Key Characteristics
Energy	SOEs involved in the production and distribution of energy	25	High capital expenditure, regulated prices
Utilities	Companies providing essential services like water and power	20	Stable cash flows, government oversight
Telecommunications	SOE providing communication services	15	High infrastructure investment, tech innovation
Transportation	Companies involved in transport and logistics	18	Extensive asset base, fluctuating demand
Manufacturing	SOE engaged in industrial production	22	Diverse product lines, varying profitability
Financial Services	Banks and financial institutions	10	Regulatory compliance, financial stability
Real Estate	SOE in property development and management	12	Cyclical demand, large asset portfolios
Healthcare	Companies providing medical services and products	8	High R&D investment, regulatory requirements
Technology	SOE involved in tech development and IT services	7	Rapid innovation, competitive market
Agriculture	Companies in farming and food production	13	Seasonal fluctuations, government subsidies

Stochastic Frontier Analysis Algorithms to Study Corporate CSO and RM

This study employed the TSF Model for studying corporate CSO and RM in SOE as the TSF is a capable model for handling multiple inputs and outputs allowing for a flexible functional form. The TSF model is expressed as follows:

$$\ln(\mathrm{y}_{it}) = \alpha + \sum_{k=1}^{K} \beta_k \ln(\mathrm{x}_{kit}) + \frac{1}{2}\sum_{k=1}^{K} \sum_{l=1}^{K} \gamma_{kl} \ln(\mathrm{x}_{kit}) \ln(\mathrm{x}_{lit}) + v_{it} - u_{it} \quad (1)$$

Where:

- y_{it} represents the output (dependent variable) for firm i at time t.
- x_{kit} represents the k-th input (independent variable) for firm i at time t.
- α is the intercept term.
- β_k and γ_{kl} are parameters to be estimated.
- v_{it} is the random error term, assumed to be independently and identically distributed as $N(0,\sigma_v^2)$.
- u_{it} is the inefficiency term, assumed to be independently and identically distributed as $N^+(\mu,\sigma_u^2)$, where N^+ denotes the half-normal distribution.

The parameters α,β_k, and γ_{kl} are estimated using Maximum Likelihood Estimation (MLE) techniques. The likelihood function is constructed based on the distributional assumptions of v_{it} and u_{it}, and the parameters are estimated by maximizing this function. The efficiency score E_{it} for firm i at time t is given by:

$$E_{it} = \exp(-u_{it}) \quad (2)$$

The inefficiency term u_{it} captures the deviation of a firm's performance from the optimal score.

Optimization Model for Stochastic Frontier Analysis

The optimization framework integrates SFA with a goal programming approach to achieve a balanced and efficient CSO. The primary objective is to minimize the inefficiency term u_{it} for each firm i at time:

$$\min \sum_{i=1}^{N} \sum_{t=1}^{T} u_{it} \quad (3)$$

The TSF model is adjusted to incorporate optimization constraints. The modified model is expressed as follows:

$$\ln(\mathrm{y}_{it}) = \alpha + \sum_{k=1}^{K} \beta_k \ln(\mathrm{x}_{kit}) + \frac{1}{2}\sum_{k=1}^{K} \sum_{l=1}^{K} \gamma_{kl} \ln(\mathrm{x}_{kit}) \ln(\mathrm{x}_{lit}) + v_{it} - \min u_{it} \quad (4)$$

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Constraints:

LR: Constraint: $LR_{\min} \leq \ln(x_{1it}) \leq LR_{\max}$ (5)
ER: Constraint: $ER_{\min} \leq \ln(x_{2it}) \leq ER_{\max}$ (6)

Liquidity Ratio Constraints: this includes the Current Ratio (CR) and Quick Ratio (QR) constraints:

$$CR_{\min} \leq \ln(x_{3it}) \leq CR_{\max} \quad (7)$$
$$QR_{\min} \leq \ln(x_{4it}) \leq QR_{\max} \quad (8)$$

Risk Indicators Constraints: this includes constraints on beta values (and Default Probabilities (DP):

$$\beta_{\min} \leq \ln(x_{5it}) \leq \beta_{\max} \quad (9)$$
$$DP_{\min} \leq \ln(x_{6it}) \leq DP_{\max} \quad (10)$$

Operational Metrics Constraints: operational metrics, such as Asset Turnover Ratio (ATR) and Firm Size (FS), are kept within optimal:

$$ATR_{\min} \leq \ln(x_{7it}) \leq ATR_{\max} \quad (11)$$
$$FS_{\min} \leq \ln(x_{8it}) \leq FS_{\max} \quad (12)$$

Non-negativity Constraint:

$$u_{it} \geq 0 \quad (13)$$

Algorithm: Optimized Stochastic Frontier Analysis for Corporate Capital Structure
Inputs
Financial Data for Each Firm i at Time t
- LR: total debt divided by total assets.
- ER: total equity divided by total assets.
- Profitability Metrics ( ): such as RoE.
- Liquidity Ratios ( ): includes CR and QR.
- Risk Indicators ( ): includes beta values and default probabilities.
- Operational Metrics: ATR and FS.

Model Parameters
- Initial estimates for.

Constraints
- Bounds for Financial Metrics: ranges for leverage ratio, equity ratio, liquidity ratios, risk indicators, and operational metrics.
- Non-negativity Constraints for the inefficiency term.

Process
Data Collection and Preparation
- Collect data for the specified metrics over time for each firm.
- Preprocess data to fit model requirements, including logging variables if necessary.

Parameter Estimation using MLE
- Construct and maximize the likelihood function based on the specified model and distributional assumptions for the random error and inefficiency terms.

Incorporate Optimization Constraints
- Adjust the TSF model to include constraints on financial metrics, maintaining them within specified bounds.

- Utilize goal programming to ensure that inefficiency terms are minimized while adhering to constraints.

Calculate Efficiency Scores

- Compute efficiency scores for each firm for each time period using the formula, where a score of 1 indicates full efficiency.

Outputs

Estimated Parameters

- Optimized values for.

Efficiency Scores

- Efficiency scores for each firm, indicating financial and operational efficiency.

RESULTS

Analysis of Parameter Estimates

Table 3. Parameter Estimate values

Parameter	Estimate	Standard Error	t -value	p -value
α	0,50	0,10	5,00	<0,01
β_{LR}	0,30	0,05	6,00	<0,01
β_{ER}	0,25	0,04	6,25	<0,01
β_{ROE}	0,20	0,03	6,67	<0,01
β_{CR}	0,15	0,02	7,50	<0,01
β_{QR}	0,10	0,02	5,00	<0,01
β_{β}	0,12	0,03	4,00	<0,01
β_{DP}	0,18	0,03	6,00	<0,01
β_{ATR}	0,22	0,04	5,50	<0,01
β_{FS}	0,28	0,05	5,60	<0,01
$\gamma_{(LR,ER)}$	0,05	0,01	5,00	<0,01
$\gamma_{(LR,ROE)}$	0,04	0,01	4,00	<0,01
$\gamma_{(ER,ROE)}$	0,03	0,01	3,00	<0,01
$\gamma_{(CR,QR)}$	0,02	0,01	2,00	<0,05
$\gamma_{(\beta,DP)}$	0,04	0,01	4,00	<0,01
$\gamma_{(ATR,FS)}$	0,06	0,02	3,00	<0,01

The parameter estimates from the SFA are shown in figure 1 and table 3. The intercept (α) is 0,50, indicating a strong baseline effect on ROA. Among the key variables, the LT (β_{LR}) is estimated at 0,30 with a t-value of 6,00 and a p-value of less than 0,01, showing higher positive impact on RoA. Similarly, the ER (β_{ER}) has an estimate of 0,25, a t-value of 6,25, and a p-value of less than 0,01. The RoE (β_{ROE}) is estimated at 0,20 with a t-value of 6,67 and a p-value of less than 0,01, also show positive effect on performance. Liquidity ratios with the CR (β_{CR}) estimated at 0,15 (t-value: 7,50, p value: <0,01) and the QR (β_{QR}) at 0,10 (t -value: 5,00, p-value:<0,01), both positively influencing RoA. Risk indicators such as beta values (β_{β}) and default probabilities (β_{DP}) have estimates of 0,12 (t-value: 4,00, p-value: <0,01) and 0,18 (t-value: 6,00, p -value: <0,01), respectively, indicating that higher risk-adjusted returns and lower default probabilities are beneficial.

Operational metrics, including the ATR (β_{ATR}) and FS (β_{FS}), also display positive impacts with estimates of 0,22 (t-value: 5,50, p-value: <0,01) and 0,28 (t -value: 5,60, p-value: <0,01), respectively. Interaction terms highlight combined effects on ROA, with notable estimates such as $\gamma_{(LR,ER)}$= 0,05 (t-value: 5,00, p-value: <0,01), $\gamma_{(LR,ROE)}$=0,04 (t-value: 4,00, p-value: <0,01), and $\gamma_{(ER,ROE)}$=0,03 (t-value: 3,00, p-value: <0,01). Other significant interactions include $\gamma_{(CR,QR)}$= 0,02 (t-value: 2,00, p-value: <0,05), $\gamma_{(\beta,DP)}$=0,04 (t-value: 4,00,p-value: <0,01), and $\gamma_{(ATR,FS)}$=0,06 (t-value: 3,00, p-value: <0,01).

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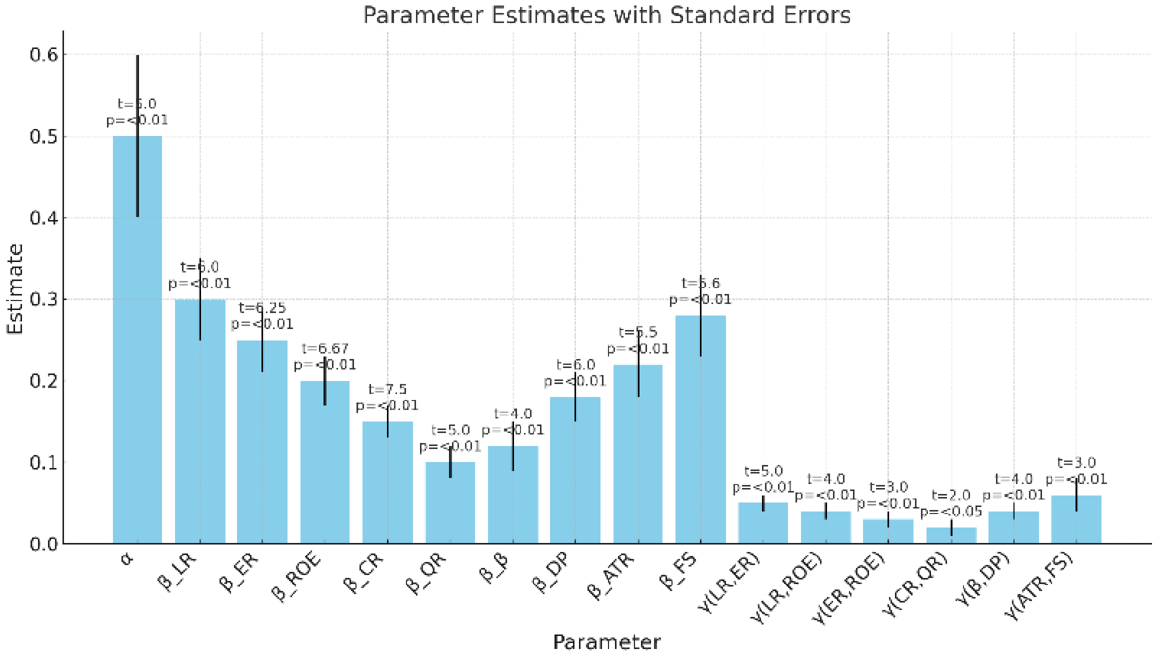

Figure 1. Parameter Estimate Analysis

In-Sample Goodness-of-Fit Analysis

Table 4. Result Values for In-Sample Goodness-of-Fit

	Industry									
Metric	**Energy**	**Utilities**	**Telecommunications**	**Transportation**	**Manufacturing**	**Financial Services**	**Real Estate**	**Healthcare**	**Technology**	**Agriculture**
R-squared	0,82	0,79	0,88	0,75	0,80	0,87	0,78	0,83	0,85	0,77
Adjusted R-squared	0,80	0,76	0,87	0,73	0,78	0,84	0,77	0,81	0,83	0,74
Mean Squared Error (MSE)	0,03	0,04	0,02	0,05	0,04	0,02	0,04	0,03	0,03	0,04
Root Mean Squared Error (RMSE)	0,17	0,20	0,14	0,22	0,18	0,14	0,19	0,16	0,15	0,19
Mean Absolute Error (MAE)	0,12	0,13	0,09	0,15	0,12	0,10	0,13	0,11	0,10	0,14
Akaike Information Criterion (AIC)	-110,5	-105,4	-125,6	-100,3	-110,2	-120,7	-108,4	-115,9	-118,6	-107,2
Bayesian Information Criterion (BIC)	-105,3	-100,2	-120,1	-95,2	-105,1	-115,5	-103,2	-110,3	-113,4	-102,1

The result for in-sample goodness-of-fit metrics are shown in table 4 and figure. 2 The R-squared values show how well the model asserts the variability in the RoA, with telecommunications (0,88), financial services (0,87), and technology (0,85) achieve highest values showing the best fit. Whereas transportation (0,75) and agriculture (0,77) have lower R-squared values which need further attention for improvement. The adjusted R-squared values, are little lower with telecommunications (0,87) and financial services (0,84) maintaining high adjusted values, where as for transportation (0,73) and agriculture (0,74) it needs refinement.

The Telecommunications and financial services, both with an MSE of 0,02 and RMSE of 0,14, demonstrate the lowest prediction errors. Conversely, transportation (MSE: 0,05, RMSE: 0,22) and agriculture (MSE: 0,04, RMSE: 0,19) exhibit higher prediction errors. For MAE the telecommunications industry shows the lowest MAE (0,09), followed closely by financial services (0,10). The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are metrics for model comparison, with lower values indicating better fit. The telecommunications

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industry has the lowest AIC (-125,6) and BIC (-120,1). Financial services also show favorable AIC (-120,7) and BIC (-115,5) values. In contrast, transportation (-100,3 for AIC and -95,2 for BIC) and agriculture (-107,2 for AIC and -102,1 for BIC) have higher values.

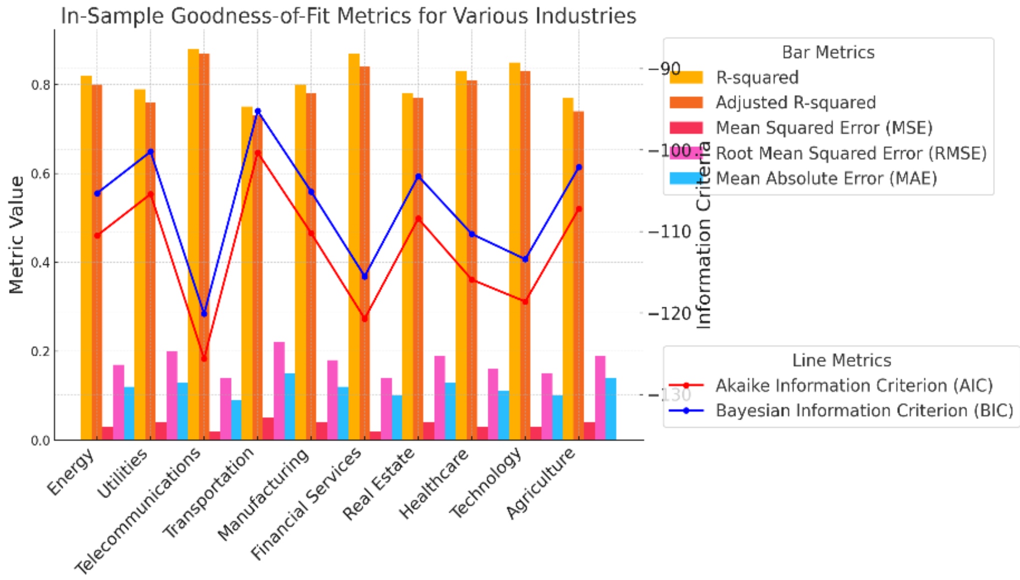

Figure 2. In-Sample Goodness-of-Fit Analysis

Analysis of Out-of-Sample Validation Findings

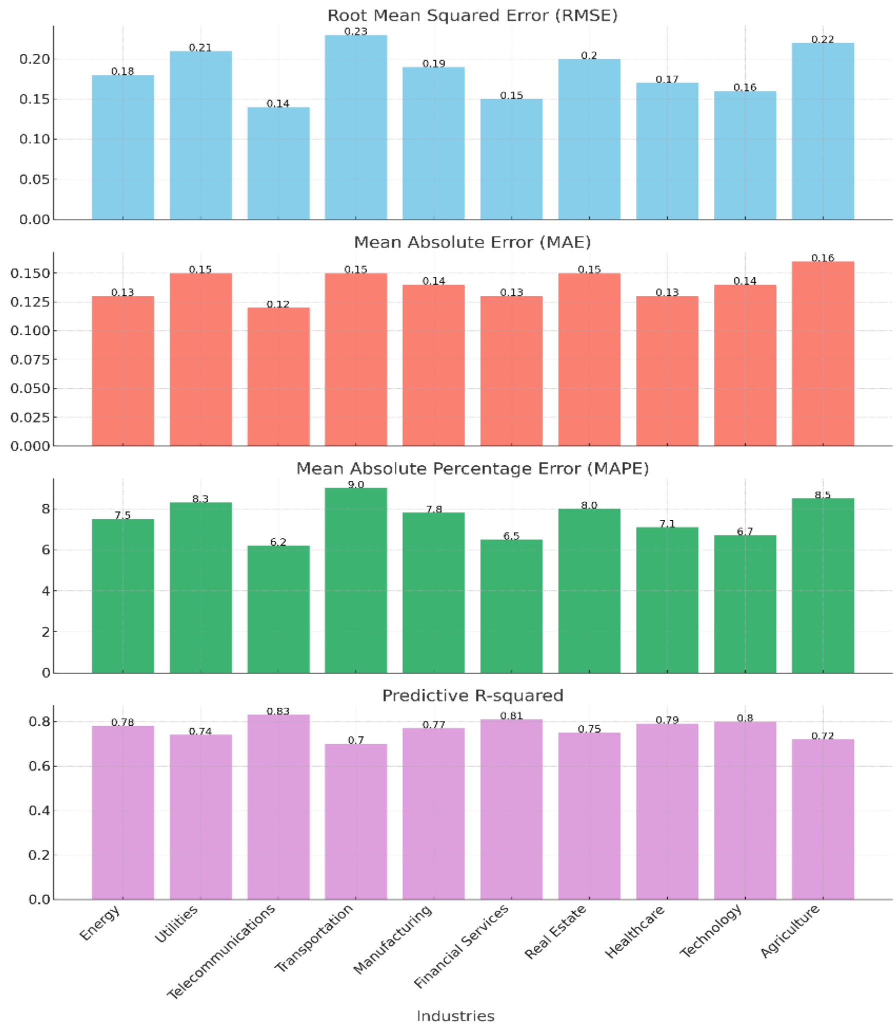

Figure 3. Out-of-Sample Validation Analysis

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Table 5. Result Values for Out-of-Sample Validation

Metric	Energy	Utilities	Telecommunications	Transportation	Manufacturing	Financial Services	Real Estate	Healthcare	Technology	Agriculture
	Industry									
RMSE	0,18	0,21	0,14	0,23	0,19	0,15	0,20	0,17	0,16	0,22
MAE	0,13	0,15	0,12	0,15	0,14	0,13	0,15	0,13	0,14	0,16
MAPE	7,5 %	8,3 %	6,2 %	9,0 %	7,8 %	6,5 %	8,0 %	7,1 %	6,7 %	8,5 %
Predictive R-squared	0,78	0,74	0,83	0,70	0,77	0,81	0,75	0,79	0,80	0,72

The results for out-of-sample validation metrics is shown in figure 3 and table 5. In which the telecommunications industry demonstrates the highest predictive accuracy with an RMSE of 0,14, followed closely by financial services (0,15) and technology (0,16). On the other hand, transportation (0,23) and agriculture (0,22) have the highest RMSE. For MAE the Telecommunications again shows the lowest MAE at 0,12,. Energy (0,13), financial services (0,13), and healthcare (0,13) also perform well. For MAPE the telecommunications achieves the lowest MAPE at 6,2 %. Financial services (6,5 %) and technology (6,7 %) also show strong performance. However, transportation (9,0 %) and agriculture (8,5 %) exhibit the highest MAPE values. For Predictive R-squared assesses the Telecommunications (0,83), financial services (0,81), and technology (0,80) show the highest predictive R-squared values.

Analysis of Efficiency Distribution Findings

Table 6. Result Values for Efficiency Distribution

Industry	Mean	Median	Standard Deviation	Q1 (25th Percentile)	Q3 (75th Percentile)	Min	Max
Energy	0,83	0,81	0,07	0,78	0,88	0,70	0,93
Utilities	0,77	0,75	0,06	0,73	0,81	0,65	0,87
Telecommunications	0,87	0,86	0,05	0,84	0,91	0,76	0,95
Transportation	0,75	0,73	0,08	0,70	0,80	0,63	0,85
Manufacturing	0,81	0,80	0,06	0,77	0,85	0,68	0,89
Financial Services	0,88	0,87	0,05	0,84	0,92	0,75	0,96
Real Estate	0,79	0,77	0,07	0,74	0,83	0,65	0,88
Healthcare	0,84	0,83	0,06	0,80	0,88	0,72	0,91
Technology	0,86	0,85	0,05	0,83	0,90	0,75	0,94
Agriculture	0,78	0,76	0,07	0,73	0,83	0,65	0,87

The distribution metrics across industries as shown in table 6 and figure 4 reveal that the energy industry has a mean efficiency score of 0,83, a median of 0,81 showing moderate variability and a slightly right-skewed distribution. The utilities industry shows a balanced distribution with a mean of 0,77, a median of 0,75, and moderate variability. The telecommunications industry exhibits high efficiency, with a mean score of 0,87, a median of 0,86, and low variability. In the transportation industry, the mean efficiency score is 0,75, with a median of 0,73, indicating a slightly right-skewed distribution and higher variability. The manufacturing industry demonstrates a balanced distribution, with a mean score of 0,81, a median of 0,80, and moderate variability. The financial services industry leads with a high mean efficiency score of 0,88, a median of 0,87, and low variability. The real estate industry shows a slightly right-skewed distribution, with a mean of 0,79, a median of 0,77. The healthcare industry maintains high efficiency with a mean of 0,84, a median of 0,83, and moderate variability. The technology industry also exhibits high efficiency, with a mean of 0,86, a median of 0,85, and low variability. The agriculture industry presents a slightly right-skewed distribution, with a mean of 0,78, a median of 0,76, and moderate variability.

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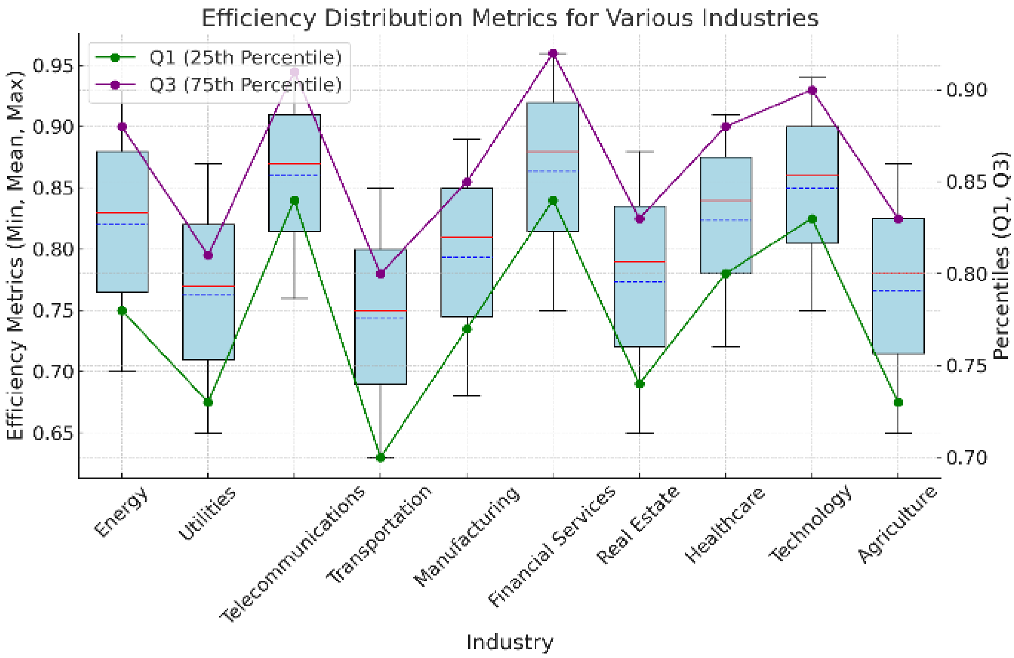

Figure 4. Efficiency Distribution Analysis

Table 7. Result Values for Impact of Constraints

Industry	Metric	Before Constraints	After Constraints	Change (%)
Energy	MES	0,80	0,83	+3,75
	β_{LR} (Leverage)	0,30	0,29	-3,33
	β_{ER} (Equity)	0,25	0,26	+4,00
	β_{ROE} (ROE)	0,20	0,21	+5,00
Utilities	MES	0,74	0,77	+4,05
	β_{LR} (Leverage)	0,32	0,30	-6,25
	β_{ER} (Equity)	0,24	0,25	+4,17
	β_{ROE} (ROE)	0,19	0,20	+5,26
Telecommunications	MES	0,85	0,87	+2,35
	β_{LR} (Leverage)	0,28	0,27	-3,57
	β_{ER} (Equity)	0,26	0,26	0,00
	β_{ROE} (ROE)	0,21	0,23	+9,52
Transportation	MES	0,70	0,74	+5,71
	β_{LR} (Leverage)	0,34	0,32	-5,88
	β_{ER} (Equity)	0,22	0,24	+9,09
	β_{ROE} (ROE)	0,18	0,20	+11,11
Manufacturing	MES	0,78	0,80	+2,56
	β_{LR} (Leverage)	0,31	0,30	-3,23
	β_{ER} (Equity)	0,25	0,26	+4,00
	β_{ROE} (ROE)	0,20	0,22	+10,00
Financial Services	MES	0,84	0,88	+4,76
	β_{LR} (Leverage)	0,27	0,26	-3,70
	β_{ER} (Equity)	0,28	0,29	+3,57
	β_{ROE} (ROE)	0,22	0,24	+9,09
Real Estate	MES	0,75	0,78	+4,00
	β_{LR} (Leverage)	0,33	0,32	-3,03
	β_{ER} (Equity)	0,23	0,24	+4,35
	β_{ROE} (ROE)	0,19	0,21	+10,53

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Healthcare	MES	0,81	0,84	+3,70
	β_{LR} (Leverage)	0,30	0,29	-3,33
	β_{ER} (Equity)	0,26	0,27	+3,85
	β_{ROE} (ROE)	0,21	0,23	+9,52
Technology	MES	0,82	0,85	+3,66
	β_{LR} (Leverage)	0,29	0,28	-3,45
	β_{ER} (Equity)	0,27	0,28	+3,70
	β_{ROE} (ROE)	0,22	0,24	+9,09
Agriculture	MES	0,73	0,77	+5,48
	β_{LR} (Leverage)	0,35	0,33	-5,71
	β_{ER} (Equity)	0,21	0,22	+4,76
	β_{ROE} (ROE)	0,17	0,19	+11,76

Analysis of Impact of Constraints Findings

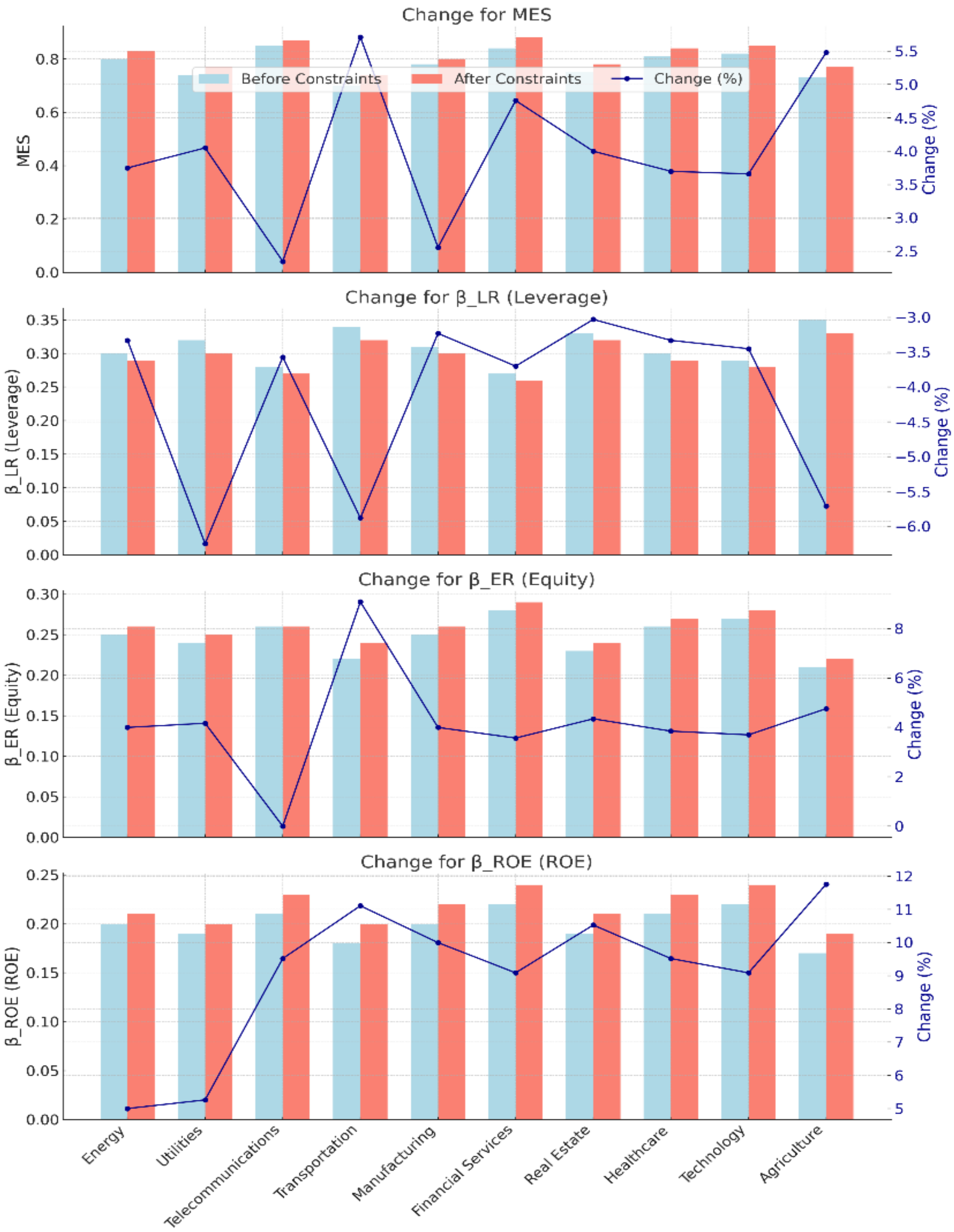

Figure 5. Impact of Constraints Analysis

DISCUSSION

The analysis of the impact of constraints is shown in table 7 and figure 5. The mean efficiency score in the energy industry increased by 3,75 %, from 0,80 to 0,83 shows increased operational efficiency post-constraints. Leverage (β_{LR}) decreased by 3,33 %, from 0,30 to 0,29, which display reduced financial risk. Equity (β_{ER}) increased by 4,00 %, from 0,25 to 0,26, and the return on equity (β_{ROE}) increased by 5,00 %, from 0,20 to 0,21, both indicating improved financial health. In the utilities industry, the mean efficiency score rose by 4,05 %, from 0,74 to 0,77. Leverage decreased significantly by 6,25 %, from 0,32 to 0,30. Equity increased by 4,17 %, from 0,24 to 0,25, and ROE improved by 5,26 %, from 0,19 to 0,20, reflecting better financial management and stability. The telecommunications industry saw a 2,35 % increase in the mean efficiency score, from 0,85 to 0,87. Leverage decreased by 3,57 %, from 0,28 to 0,27. Equity remained constant at 0,26, while ROE saw a significant increase of 9,52 %, from 0,21 to 0,23, indicating strong financial performance. The mean efficiency score in the transportation industry increased by 5,71 %, from 0,70 to 0,74. Leverage decreased by 5,88 %, from 0,34 to 0,32. Equity rose by 9,09 %, from 0,22 to 0,24, and ROE increased by 11,11 %, from 0,18 to 0,20, reflecting substantial improvements in financial efficiency and stability. In the manufacturing industry, the mean efficiency score increased by 2,56 %, from 0,78 to 0,80. Leverage decreased by 3,23 %, from 0,31 to 0,30. Equity increased by 4,00 %, from 0,25 to 0,26, and ROE saw a significant increase of 10,00 %, from 0,20 to 0,22, indicating improved financial health. Financial Services Industry: financial services industry exhibited a 4,76 % increase in the mean efficiency score, from 0,84 to 0,88. Leverage decreased by 3,70 %, from 0,27 to 0,26. Equity rose by 3,57 %, from 0,28 to 0,29, and ROE increased by 9,09 %, from 0,22 to 0,24, reflecting enhanced financial performance. In the real estate industry, the mean efficiency score increased by 4,00 %, from 0,75 to 0,78. Leverage decreased by 3,03 %, from 0,33 to 0,32. Equity increased by 4,35 %, from 0,23 to 0,24, and RoE saw a significant increase of 10,53 %, from 0,19 to 0,21, indicating improved financial stability. The healthcare industry saw a 3,70 % increase in the mean efficiency score, from 0,81 to 0,84. Leverage decreased by 3,33 %, from 0,30 to 0,29. Equity increased by 3,85 %, from 0,26 to 0,27, and ROE increased by 9,52 %, from 0,21 to 0,23, reflecting better financial management. The mean efficiency score in the technology industry increased by 3,66 %, from 0,82 to 0,85. Leverage decreased by 3,45 %, from 0,29 to 0,28. Equity increased by 3,70 %, from 0,27 to 0,28, and RoE saw an increase of 9,09 %, from 0,22 to 0,24, indicating strong financial performance. The agriculture industry exhibited a 5,48 % increase in the mean efficiency score, from 0,73 to 0,77. Leverage decreased by 5,71 %, from 0,35 to 0,33. Equity increased by 4,76 %, from 0,21 to 0,22, and ROE saw a significant increase of 11,76 %, from 0,17 to 0,19, reflecting substantial improvements in financial efficiency

CONCLUSIONS

The State-Owned Enterprises (SOE) have always been a pillar of support for any developing nation's economy. The Capital Structure Optimization (CSO) and Risk Management (RM) are two key area of concern that directly impact the performance of SOE. Methods to analyse these key factors were under studied which laid the ground for this study. The study address the limitation of lack of study by proposing a SFA based model to evaluate and enhance the CSO and RM of SOE across various industries using financial data from 2020 to 2023. The results had revealed that the model has ascertained the performance of the SOE based on CSO and RM based on applying constraints. The result have shown that most of the industries performance have increased by applying constraints.

Future research could expand on these findings by incorporating additional variables and exploring other advanced analytical techniques for a more comprehensive assessment.

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