

Financial Factors and the Probabilistic Prediction of Financial Failure: Evidence from the Central Public Sector Enterprises in India

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ABSTRACT

The present, obvious growing failure of the enterprises in India and the factors that push them to fail obviously call the sustainable financial health of these enterprises into question. The policies, regulations, and new strategies should be developed to help management and policy makers to examine the factors that affect the likelihood of failure. For the purpose of this study, 27 Heavy, Medium, and Light Engineering Enterprises were chosen as a sample, with a ten-year study period. 15 variables were chosen that are identically correlated with the occurrence of failure via Principal Component Analysis. Logistic regression was used to examine these variables. The result of logistic regression has an accuracy of 83.9% in predicting the failure. Financial health was also examined using the Altman Z score model. The failure may be avoided if influencing factors are timely established and the correct prediction model is applied to enhance the financial situation.

Keywords: *Bankruptcy prediction; Central public sector enterprises; Financial failure; Logistic regression.*

1.0 Introduction

Because of the valued contribution of the Central Public Sector Enterprises (CPSEs) to the Indian economy over the last seven decades, India has ranked high among the world's top industrialised nations. However, given the way the public

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sector has grown, it is always a source of controversy. Many CPSEs have underperformed their budgeted targets; as a result, these businesses have failed or are on the verge of failing due to poor profitability (Mishra, 1986; Venkatachalam, 1988). These inefficient CPSEs are becoming liabilities for the government (Talha, 1986), raising serious concerns about their sustainability. The failure of any enterprise has a significant impact on stakeholders in particular, as well as the entire economy in general (McKee & Lensberg, 2002; Tsai, 2008). Financial failure prediction has been a topic of debate in academic literature and business around the world. As a result of incorrect prediction and decision-making, the business may face additional financial difficulties.

The primary focus of this study was the prediction of financial failure, which is important from an economic standpoint because it can affect many stakeholders at the same time. Our paper investigates the factors that contribute to the failure of Heavy, Medium, and Light Engineering Central Public Sector Enterprises. How to predict failure by analysing the factors? In addition, the effectiveness of the logistic regression approach in prediction will be evaluated. We also aimed to assess the financial health of CPSEs in order to determine their long-term viability. We concentrated on the Heavy, Medium, and Light Engineering Central Public Sector Enterprises from India as a study sample because most studies were conducted in India and around the world on private sector organisation industries such as hospitality, construction, manufacturing, and so on, or on specific organisations in general. Only a few researchers conducted studies on public-sector enterprises to the extent of studying the problems and reasons for the poor performance by CPSEs and knowing the financial health of the CPSEs. The objectives and magnitude of operations of public sector enterprises differ significantly from those of private sector enterprises. The treatment of financial failure, insolvency, and bankruptcy is a distinct event in the context of a business model.

Recently, many researchers have used logistic regression approaches to improve the accuracy of bankruptcy prediction. Many academic studies have used traditional statistical techniques to predict financial failure and bankruptcy, such as multiple discriminant analysis and logistic regression (Kim & Zheng, 2006; Min & Jeong, 2009; Dakovic *et al.*, 2010; Koh & Killough 2010; Barreda *et al.*, 2017).

An enterprise's success or failure is determined by the interaction of numerous financial factors. A noticeable drop in profitability marks the start of a decline in business performance; sales and operating income fall, and negative stock returns are indicators of decline. Knowing the financial solvency and prospects of a company is a critical component of corporate finance. According to the Government of India's

Department of Disinvestment, ten to fifteen percent of the total gross domestic savings were declining year on year due to low savings from CPSEs.

The following is how the paper is structured: The second section examines the related literature. The research objectives are presented in the third section. The fourth section includes information about the data and methodology used. The fifth section presents the findings from the data analysis and the results of a robustness test conducted to validate the results of logistic regression method are included in the section. In the sixth section, we summarise and conclude the paper with scope for further research.

2.0 Review of Literature

2.1 Central public sector enterprises

Several academic researches on CPSEs in India intended to examine the various areas that need improvement (Mishra, 1986; Seetharaman, 2000). Talha (1986) examined the existing trend of CPSE profitability and reached the conclusion that the CPSEs' performance was unsatisfactory and their social and economic returns were quite limited. Gilker (1999) and Seetharaman (2000) assessed the performance of the CPSEs using financial statements and financial ratios. Beena (2012) examined the financial statements and financial ratios, as well as the capital structure, investment mix, and the leader's perception. All of the preceding studies concluded with remarks about the CPSEs' poor performance. Gilker (1999); Ritu (2002) used the Altman Z score model to determine the financial health of CPSEs and concluded that the financial health of the enterprises are mostly in a distress zone.

2.2 Factors influencing the probability of financial failure and prediction model

Beaver (1966) investigated 30 financial ratios as predictors of bankruptcy and classified them into six groups. He predicted corporate bankruptcy by using multivariate and univariate analysis. Altman (1968) popularised the bankruptcy prediction model (Z-Score) by relying on the Multiple Discriminant Analysis (MDA) technique. Altman examined 22 ratios in this study, which were classified as liquidity, profitability, leverage, solvency and activity. The Z-score is an indicator that classifies companies into three distinct groups based on their score in order to determine their financial health. Ohlson (1980) conducted another such significant study in the field of bankruptcy prediction. He used the traditional logistic regression method to forecast the firm's financial health. Altman and Narayanan (1997) investigated the active role of financial ratios as well as logistic regression, MDA, and probit models in predicting failure risks. A firms' failure is the result of a whole set of endogenous as well as exogenous factors.

Following Altman's research, Beaver; McNichols & Rhie (2005) predicted bankruptcy using financial ratios from financial statements. Many scholars, however, have developed various models to study the phenomenon of bankruptcy. Dakavic *et al.*, 2010 created the statistical model for predicting Norwegian organisation bankruptcy.

The study investigates the functional relationship of financial variables. The model observed heterogeneity between different sectors in the generalised line mixed model. Barreda *et al.*, (2017) recently investigated the key financial variables that predict bankruptcy of hospitality firms in the US equity market. The study looked at both bankrupt and non-bankrupt businesses. MDA found to outperform the logit model in terms of overall bankruptcy prediction accuracy. Mu-Yen, (2011); Gregova *et al.*, (2020) have applied hybrid approaches using statistical and machine learning techniques to predict the bankruptcy.

In the present literature, we noted that very few studies were carried out on CPSEs to predict their financial status and probable failure. Based on the literature study, financial variables such as profitability, liquidity, operational efficiency, and so on were regarded as important factors for bankruptcy by the researchers. The literature also tells us how the researchers use various statistical methods to predict the failure of a sample organisation or industry.

As a result, our current study is a simple attempt to fill a gap in the study of CPSEs. Unlike in the study of other types of business models, bankruptcy is not a common occurrence in the case of CPSEs. The CPSEs must go through a revival and restructuring phase, after which they may be merged with better performing CPSEs, and if not, privatisation is the only option. As a result, it is critical to investigate the factors causing CPSEs to fail financially and to assess the model that will accurately predict the failure. By doing so, the long-term consequences of poor financial conditions can be mitigated. The findings will help the enterprises to improvise their financial health to achieve sustainability.

3.0 Research Questions

The objective is to study the factors leading to the prediction of failure and measures of sustainable financial health of selected CPSEs.

- To study the financial factors influencing the failure
- To predict the probability of failure and assess the effectiveness of the model in explaining the accuracy in predicting the failure.
- To measure the financial health of the CPSEs by using Altman's Z score model

4.0 Research Methodology and Data

4.1 Sample data selection

The study is based on data from 27 Heavy, Medium, and Light Engineering CPSEs from 2009-10 to 2018-19 using the census method of sampling (Table 1).

Table 1: List of Sample CPSEs

Sr. No.	Name of CPSEs	Category
1	Bharat Heavy Electricals Ltd.	Heavy Engineering
2	Bharat Wagon & Engg. Co. Ltd.	Heavy Engineering
3	BHEL Electrical Machines Ltd.	Heavy Engineering
4	Braithwaite & Co. Ltd.	Heavy Engineering
5	Burn Standard Company Ltd.	Heavy Engineering
6	Heavy Engineering Corpn. Ltd.	Heavy Engineering
7	Tungabhadra Steel Products Ltd.	Heavy Engineering
8	Andrew Yule & Company Ltd.	Medium & Light Engineering
9	Balmer Lawrie & Co. Ltd.	Medium & Light Engineering
10	BEL Optronics Devices Ltd.	Medium & Light Engineering
11	Bharat Dynamics Ltd.	Medium & Light Engineering
12	Bharat Electronics Ltd.	Medium & Light Engineering
13	Bharat Pumps & Compressors Ltd.	Medium & Light Engineering
14	Central Electronics Ltd.	Medium & Light Engineering
15	Electronics Corpn. Of India Ltd.	Medium & Light Engineering
16	Hindustan Cable Ltd.	Medium & Light Engineering
17	HMT Bearings Ltd.	Medium & Light Engineering
18	HMT Chinar Watches Ltd.	Medium & Light Engineering
19	HMT Ltd.	Medium & Light Engineering
20	HMT Machine Tools Ltd.	Medium & Light Engineering
21	HMT Watches Ltd.	Medium & Light Engineering
22	I T I Ltd.	Medium & Light Engineering
23	Instrumentation Ltd.	Medium & Light Engineering
24	Rajasthan Electronics And Instruments Ltd.	Medium & Light Engineering
25	Richardson & Cruddas (1972) Ltd.	Medium & Light Engineering
26	Scooters India Ltd.	Medium & Light Engineering
27	Vignyan Industries Ltd.	Medium & Light Engineering

Source: Public Enterprise Survey 2017-18: Vol. II, Government of India, New Delhi

The selected samples are further classified as either failure or non-failure (Beaver 1966; Altman, 1968; Kim & Zheng, 2006; Min & Jeong, 2009; Barreda *et al.*,

2017) (Table 2). According to BRPSE, “An enterprise is considered a failure if it has accumulated losses in any fiscal year equal to fifty percent or more of its average net worth during the four years immediately preceding such fiscal year.” In addition, an enterprise designated as a sick company under the “Sick Industrial Companies (Special Provisions) Act, 1985” (SICA) is referred to BRPSE for revival and restructure. In this paper, we have made reference to the above mentioned definition and carefully chosen those Heavy, Medium & Light Engineering Enterprises that are referred to BRPSE. These enterprises are referred to as failure sample CPSEs, while non-failure sample CPSEs are referred to as those who have made a net profit in the previous four fiscal years.

Table 2: The Number of Observations of Classification of Samples in Study Period

Year	Classification		Total
	Failure	Non-failure	
2009-10	17	10	27
2010-11	17	10	27
2011-12	20	7	27
2012-13	19	8	27
2013-14	18	9	27
2014-15	12	15	27
2015-16	11	16	27
2016-17	10	17	27
2017-18	11	16	27
2018-19	11	16	27

Source: Public Enterprise Survey Various Issues, Government of India, New Delhi

4.2 Data set

To avoid modeling issues, the financial statements in this study are derived from the PE survey published by the Department of Public Enterprises, Government of India between 2009-10 and 2018-19.

4.3 Variable collection & selection

The variables chosen for the study are based on previous research done in this field by various researchers. The ratios were chosen based on their occurrence in the literature as well as their potential relevance to the study. Table 3 displays the ratios considered as independent variables.

Table 3: The Key Independent Variables

	Variable ID	Variable	Description
Profitability	P 1	Net Profit Margin	Net Profit (PAT)/Total Sales
	P 2	Return on Assets	Net Profit (PAT)/ Total Assets
	P 3	Retained profit to total assets	retained earnings/total assets
	P 4	EBIT to total assets	Earnings before interest and taxes/total assets
	P 5	Sales to total assets	sales/total assets
Liquidity	L 1	Current ratio	Current Assets/Total Liabilities
	L 2	Working capital to Total Assets	working capital/total assets
	L 3	Total current liabilities to total assets	Total Current liabilities/Total Assets
Solvency	Sol1	Debt Equity	Shareholders fund/Total Debt
	Sol 2	Long term debt to total assets	Long term debt (Total Liabilities)/Total Assets
Managerial efficiency	M 1	Gross value added (GVA) to total assets	Gross value added (GVA)/ total assets
	M 2	Gross value added to capital employed	Gross value added/capital employed
	M 3	Sales to labour cost	Sales/Labour cost
Capital output ratio	CO	Capital output ratio	Capital investment/total output
Growth Ratio	Gr 1	Market value of equity or book value of equity to total debt/liabilities	Market value of equity or book value of equity/total debt/liabilities

Source: Authors' compilation

4.3.1 Dependent variable

The failure of the CPSE is a binary variable that considers a value of 1, a failure and 0, a non-failure CPSE.

$$y = \begin{cases} 1 & \text{failure} \\ 0 & \text{non failure} \end{cases}$$

4.4 Methods used for prediction

4.4.1 Logistic regression

Logistic regression tries to model the unilateral dependence of variables, where the explored dependent variables can be binary, ordinal, or categorical, and the predictor variable can be categorical or continuous. One such method employs a binary dependent

variable as well as a dummy variable for failure. If the CPSE is non-failure, the dummy variable is 0, and if it is a failure, it is 1.

The probability estimation of this model will be between 0 and 1.

$$(y = 1/x) = (y = 1/x_1, x_2, \dots, k) \text{ (Wooldridge, 2014).} \quad \dots (1)$$

Because the dependent variable is binary, it does not satisfy the linear regression normality assumption, linearity, and homoscedasticity of independent variables. Because failure is observed on an ordinal scale, the Logit model is the best technique. The maximising problem is estimated by determining the co-efficient that provides the highest probability of estimating dependent variables. The greater the variable x will result in increases or decreases in the probability of variable y in Logit model.

4.4 2 Altman Z score model (1968)

In the model, the Z score which is a survival indicator, classifies companies based on their solvency position. The higher the value of the Z score is, the lower the risk of bankruptcy. A low or negative Z score indicates the high likelihood of failure of a firm. Altman showed that companies with a Z score of less than 1.81 (distress zone) are highly risky and likely to go bankrupt; companies with a Z score of more than 2.99 (safe zone) are healthy and stable companies where bankruptcy is unlikely to occur. Companies that have a Z score from 1.81 to 2.99 are in the gray zone with uncertain results and bankruptcy is not easily predicted one way or the other (Altman, 1968). The original Altman Z Score (1968) is as follows:

$$Z = 0.012(X_1) + 0.014(X_2) + 0.033(X_3) + 0.006(X_4) + 0.999(X_5) \quad \dots (2)$$

Where,

X_1 = working capital/total assets,

X_2 = retained earnings/total assets,

X_3 = earnings before interest and taxes/total assets,

X_4 = market value of equity/book value of total debt,

X_5 = sales/total assets

Financial failure never happens all at once, but rather in stages: first, the output volume falls, preceded by a drop in profitability, a rise in working capital, a deterioration of the capital structure, and finally, financial failure. The summary statistics for the variables chosen for measuring and evaluating financial failure were described. Table 4 provides descriptive statistics on non-failure and failure enterprises; the scores for the relevant item are quantified for each sample CPSEs, and the appropriate item's average is taken. The average score of the CPSEs classified as failure or non-failure is then used to compute the mean, standard deviation, and variance.

Table 4: Summary Statistics

Variable ID	Non Failure			Failure		
	Mean	S D	Variance	Mean	S D	Variance
P 1	13.61	24.83	127.10	-22.78	55.05	3030.22
P 2	8.40	16.86	146.55	-76.51	269.09	72407.66
P 3	0.05	0.03	0.00	-5.41	7.87	61.93
P 4	0.08	0.09	0.01	-2.39	4.01	16.05
P 5	2.78	0.77	0.59	0.57	0.49	0.24
L 1	1.56	0.56	0.31	0.65	0.74	0.54
L 2	0.23	0.19	0.04	-1.20	2.76	7.63
L 3	0.40	0.15	0.02	2.92	2.73	7.43
Sol 1	0.02	1.92	3.69	1.01	2.40	5.77
Sol 2	0.08	0.12	0.02	6.00	16.02	256.79
M 1	0.31	0.34	0.11	0.44	1.44	2.06
M 2	54.98	84.38	7119.20	61.10	171.42	29384.69
M 3	7.41	5.80	33.67	18.84	21.25	451.53
CO	2.53	1.97	3.90	-1.48	4.87	23.75
Gr 1	0.00	0.00	0.00	1.44	3.14	9.83

Source: Authors' compilation

The descriptive statistics in Table 4, the mean value of net profit margin in non-failure CPSEs is 13.61. However, in the case of failed CPSEs, the value is -22.78. The mean value of liquidity variables also demonstrates failure CPSEs' poor performance. There is an area where failure CPSEs perform quite well; the mean value of GVA to capital employed is higher than for non-failure CPSEs. Based on the current findings, the selected CPSEs have underperformed on the chosen financial parameters, they outperform on the social front by adding gross value to the capital employed. The failure CPSEs had a higher standard deviation than the non-failure CPSEs. This suggests that failure CPSEs have higher levels of deviation and volatility in their performance. The high variance figures indicate that failure enterprises are less consistent in their financial performance. The variance results showcase ineffective and inefficient operations. There is a huge distinction in the performance. The failure CPSEs have performed poorly on all fronts. The CPSEs' weak performance is causing them to fail financially. Nevertheless, this can be subjected to further statistical analysis and measurement of the appropriate model to predict failure.

5.0 Result and Analysis

In this section, our main aim is to predict financial failure by using the logistic regression approach. In this, firstly, we start with principal component analysis to identify the factors influencing the failure.

5.1 Measure of factor influencing the probability of failure

In this section, we have identified the factors influencing financial failure through principal component analysis.

5.1.1 Principal component analysis

The KMO test measures the sample adequacy, and Bartlett's tests measure the relationship among the attributes. Table 5 represents the tests' statistics, in the study; it is 0.857 which is a good score to continue the analysis of data. Furthermore, Bartlett's test of sphericity results shows the chi-square (χ^2) statistics as 19107.138 with 540 degrees of freedom. This value is significant at a 0.05 level i.e., $p < 0.05$. Thus, the results of both the tests indicate that factor analysis may be considered an appropriate technique for analysing further data.

Table 5: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.857
Bartlett's Test of Sphericity	Approx. Chi-Square	19107.138
	Df	540
	Sig.	.000

Source: Authors' compilation

Table 6 shows the outcomes of the initial and extracted communalities. The communalities describe the proportion of variance that each variable shares with all the other variables. That is, it assesses the degree to which an attribute correlates with all the other aspects of the study. P2-Return on Assets (0.997) has the highest communalities. However, the lowest communalities are found in Gr1-Market value of equity or book value of equity to total debt/liabilities (0.630). The low communality value indicates that the variable in question is ineffective and should be removed from the factor analysis. To simplify the analysis, only variables with a communality value of 0.7 or higher were reported in this study, and variables with a communality value of less than 0.7 were dropped.

Table 6: Communalities

	Initial	Extraction
P 1	1.000	.974
P 2	1.000	.997
P 3	1.000	.981
P 4	1.000	.970
P 5	1.000	.981
L 1	1.000	.799
L 2	1.000	.942
L 3	1.000	.619
Sol 1	1.000	.769
Sol 2	1.000	.662
M 1	1.000	.644
M 2	1.000	.734
M 3	1.000	.832
CO	1.000	.861
Gr 1	1.000	.630

Source: Authors' compilation

Table 7: Total Variance Explained

Component	Initial Eigen Values			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5.227	34.847	34.847	5.227	34.847	34.847	5.227	34.847	34.847
2	3.499	23.327	58.173	3.499	23.327	58.173	3.499	23.327	58.173
3	1.627	10.847	69.020	1.627	10.847	69.020	1.627	10.847	69.020
4	1.389	9.260	78.280	1.389	9.260	78.280	1.389	9.260	78.280
5	1.156	7.707	85.987	1.156	7.707	85.987	1.156	7.707	85.987
6	0.703	4.687	90.673						
7	0.68	4.533	95.207						
8	0.31	2.067	97.273						
9	0.204	1.360	98.633						
10	0.137	0.913	99.547						
11	0.032	0.213	99.760						
12	0.022	0.147	99.907						
13	0.008	0.053	99.960						
14	0.005	0.033	99.993						
15	0.001	0.007	100.000						

Extraction Method: Principal Component Analysis.

Source: Authors' compilation

Furthermore, the attributes were examined for Eigen value, which is the total variance explained by each factor. In this study, we selected factors with Eigen values greater than 1.0.

Table 7 shows that there are five factors which have an Eigen value of more than 1.0 and the cumulative variance explained variance was 85.485%. Based on the analysis, we selected the first five principal components as a measure of profitability, liquidity, solvency, managerial efficiency and capital-output ratio.

Table 8: Rotated Component Matrix^a

	Component				
	1	2	3	4	5
P 1	0.815	-0.008	0.026	-0.051	-0.077
P 2	0.894	0.032	0.049	-0.439	0.04
P 3	0.978	0.025	-0.114	-0.069	0.082
P 4	0.966	0.129	-0.081	-0.062	0.099
P 5	0.964	0.116	-0.074	0.162	0.082
L 1	0.524	0.756	0.102	-0.524	0.177
L 2	0.148	0.953	0.051	0.02	0.098
L 3	-0.92	0.006	-0.013	-0.258	0.08
Sol 1	0.159	0.014	0.816	0.133	-0.245
Sol 2	-0.958	-0.129	-0.101	0.116	-0.052
M 1	-0.938	-0.102	-0.122	0.184	-0.072
M 2	0.262	-0.033	-0.128	-0.740	0.018
M 3	0.142	-0.081	0.542	0.711	0.078
CO	0.047	0.2	-0.284	-0.127	0.849
Gr 1	0.56	0.42	-0.279	0.406	-0.312

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.

Rotation converged in 7 iterations.

Source: Authors' compilation

As a result, Table 8 represents the components that were rotated in the first round of Varimax rotation. The results show that, of the 15 variables chosen for the study, ten variables had factor loading values greater than 0.7 and were retained in the input vector using the Kaiser normalisation criteria, while the remaining five were eliminated because their factor loading values were less than 0.7. The experiment was then run a second time with the remaining ten variables using factor analysis. The optimal solution was not realised during the second round of factor analysis. As a result

of the above analysis, the dimension reduction of diverse financial indicators such as Return on Assets (P2), Retained Profit to Total Assets (P3), EBIT to Total Assets (P4), Net Profit Margin (P1), Sales to Total Assets (P5), Working Capital to Total Assets (L2), Current Ratio (L1), Debt Equity (Sol 1), Labour cost to sales (M3), Capital output ratio (CO) are important financial ratios which influence the financial performance of the CPSEs. These are the variables that mainly push the CPSEs towards failure if not well resulted. These critical ratios were then combined to form five major components as an indicator of profitability, liquidity, solvency, managerial efficiency, and capital-output ratio.

5.2 Logistic regression

The percentage likelihood of a corporate failure is calculated using the results of this binary model. Q_1 is the proportion of failure enterprises in the sample and H_1 is the proportion of non-failure enterprises.

$$\log L = \sum_{i=1}^N w_i \log F(q_i(\alpha_i + X_i\beta)) \quad \dots (3)$$

$$y = \begin{cases} 1 & \text{failure} \\ 0 & \text{non failure} \end{cases}$$

Table 9: Analysis of Logistic Regression

	B	S. E.	Sig.	
Profitability	1.889	1.143	.016	Significant
Liquidity	.745	.316	.027	Significant
Solvency	.168	.320	.010	Significant
Managerial efficiency	.635	.571	.019	Significant
Capital Output Ratio	-.004	.317	.989	Insignificant
Constant	.177	.410	.666	
The Cox & Snell R square value is 0.625 and Nagelkerke R square value is 0.834				

Source: Authors' compilation

The logistic regression results are shown in Table 9. The co-efficient of Capital Output Ratio (-0.004) is negatively correlated and insignificant at the 5% level of significance, as are the co-efficients of profitability (1.889), liquidity (0.745), solvency (0.168), and managerial efficiency (0.635). The p value of profitability, liquidity, solvency, and managerial efficiency is less than the 5% level of significance, i.e. $p < 0.05$, indicating that these factors have a significant impact on CPSE failure. Thus, the study shows that profitability, liquidity, solvency and managerial efficiency have a significant impact on financial failure.

The logistic regression model is further fitted using the method of maximum likelihood. The Cox & Snell R square value is 0.625 and Nagelkerke R square value is 0.834 indicating that the model may be useful in practice.

5.3 Analysis of financial health using the Altman Z-score

Table 10: Analysis of Financial Health (Z Score)

Sr. No.	Name of the CPSE	Average Z Score	Standard Deviation	Co-efficient of Variance
1	Bharat Heavy Electricals Ltd.	1.57	0.14	8.62
2	Bharat Wagon & Engg. Co. Ltd.	0.24	1.24	31.48
3	BHEL Electrical Machines Ltd.	2.08	0.33	10.81
4	Braithwaite & Co. Ltd.	1.73	0.10	9.28
5	Burn Standard Company Ltd.	1.29	0.52	12.45
6	Heavy Engineering Corpn. Ltd.	-1.02	0.20	24.06
7	Tungabhadra Steel Products Ltd.	0.01	1.01	31.01
8	Andrew Yule & Company Ltd.	2.36	0.60	25.50
9	Balmer Lawrie & Co. Ltd.	2.79	0.29	10.24
10	BEL Optronics Devices Ltd.	2.85	0.22	9.02
11	Bharat Dynamics Ltd.	3.00	0.44	15.49
12	Bharat Electronics Ltd.	1.49	0.26	17.36
13	Bharat Pumps & Compressors Ltd.	1.59	0.36	22.71
14	Central Electronics Ltd.	1.37	0.36	26.07
15	Electronics Corpn. of India Ltd.	1.56	0.55	35.33
16	Hindustan Cable Ltd.	-7.12	0.73	49.86
17	HMT Bearings Ltd.	-1.52	0.88	29.19
18	HMT Chinar Watches Ltd.	-1.98	0.20	10.24
19	HMT Ltd.	0.92	0.13	18.32
20	HMT Machine Tools Ltd.	-2.00	1.21	60.77
21	HMT Watches Ltd.	-1.53	0.98	19.24
22	I T I Ltd.	1.44	0.31	21.73
23	Instrumentation Ltd.	-0.10	0.61	29.63
24	Rajasthan Electronics And Instruments Ltd.	1.55	0.61	39.28
25	Richardson & Cruddas (1972) Ltd.	-2.25	0.25	34.21
26	Scooters India Ltd.	1.07	0.14	14.93
27	Vignyan Industries Ltd.	-3.05	0.40	37.67

Source: Authors' compilation

The Altman's Z Score is used to assess the financial health of the selected CPSEs. It is found from Table 10 that BDL (3.00) is in the safe zone ($Z > 2.99$) and

BLCL (2.79) is in the gray zone ($1.80 < Z < 2.99$), whereas BEL (1.49) falls under the distress zone ($Z < 1.80$). In the case of failure CPSEs, all failed CPSEs have registered a negative Z score (e.g. HCL (-7.12), RCL (-2.25) and Instrumentation Ltd (-0.10)) are in the distress zone and their financial health is negative.

In the next couple of years, these CPSEs are certain to fail. The results also show that only Bharat Dynamics Ltd. (Z-score=3.00) is in the safe zone and four CPSEs are falling under the gray zone. The coefficient of covariance of failure CPSEs shows the inconsistency in reporting the financial performance and financial risk. Within the sample CPSEs, we observe a significant difference in financial health.

5.4 Robustness test of the model

We applied the regression analysis in a variable Z to assess the accuracy of the model when we predict the failure. The model that sets as Z is inspired by Ohlson's (1980) logistic regression model.

$$Z = \beta_0 + \beta_1 * F1 + \beta_2 * F2 + \beta_n * Fn + \varepsilon \quad \dots (4)$$

Where $\beta_0, \beta_1, \dots, \beta_n$ are regression coefficient and ε the error terms.

$$Z = 0.177 + 1.889 * F1 + 0.745 * F2 + 0.168 * F3 + 0.635 * F4 - 0.004 * F5$$

In the model, Z represents the probability of failure $p = p(\text{failure} = 1|Z) = F(Z)$. Where F is cumulative distribution (between 0 and 1), which shows the probability for failure.

$$p = F(\beta_0 + \beta_1 * F1 + \beta_2 * F2 + \beta_n * Fn) \quad \dots (5)$$

To find p, we pretend that the cumulative distribution is logically dispersed

$$F(Z) = \frac{e^Z}{1+e} \quad \dots (6)$$

In such a case the probability p may be

$$p = \frac{1}{1+e^{-Z}} \quad \dots (7)$$

The above equation can be rewritten as

$$p(x) = \frac{e^{\beta_0 + \beta_1 F1 + \beta_2 F2 + \dots + \beta_n Fp}}{1 + e^{\beta_0 + \beta_1 F1 + \beta_2 F2 + \dots + \beta_n Fp}} \quad \dots (8)$$

The estimated probability of failure

$$p(x) = \frac{e^{0.177 + 1.889F1 + 0.745F2 + 0.168F3 + 0.635F4 - 0.004F5 + 0.177F5} * 1}{1 + e^{0.177 + 1.889F1 + 0.745F2 + 0.168F3 + 0.635F4 - 0.004F5 + 0.177F5} * 1}$$

The outcome of the failure's probability estimation the enterprise's failure probability is 0.791057.

The estimated probability of non-failure

$$p(x) = \frac{e^{0.177 + 1.889F1 + 0.745F2 + 0.168F3 + 0.635F4 - 0.004F5 + 0.177F5 * 0}}{1 + e^{0.177 + 1.889F1 + 0.745F2 + 0.168F3 + 0.635F4 - 0.004F5 + 0.177F5 * 0}}$$

The result of probability estimation, the probability of non-failure of the enterprise is 0.783033.

A confusion matrix is depicted to further analyse the accuracy of the logistic regression model. The confusion matrix summarises the classification algorithm's performance.

Table 11: Confusion Matrix of Logistic Regression

	Percentage Correct	Percentage False
Non failure	75.9	22.23
Failure	83.9	14.82

Source: Authors' compilation

As per the confusion matrix analysis (Table 11), the model's correct accuracy of predicting failure is 83.9 percent, while correct accuracy in predicting non-failure is 75.9 percent of the time. Furthermore, the results show that the logistic regression model's overall efficiency in predicting accurately is 79.9 percent. According to the results, logistic regression is a good model for prediction; however, the high percentage of error rate may result in poor classification, which should be considered carefully when using the model.

The classification results sensitivity, specificity, and total error rate of the model used in this study. In this case, sensitivity is the percentage of true failure that has been identified, and specificity is the percentage of non-failure that has been correctly identified. Logistic regression model shows, sensitivity = 18.51%, specificity = 81.48% and the total error rate = 1.481% which is quite satisfactory.

6.0 Conclusion

It is critical in financial decision-making to accurately predict business failure. In the professional and academic literature, financial failure prediction is regarded as a very important and critical topic. The CPSEs are regarded as a barometer of the Indian economy. The CPSEs should be regarded as living entities, and throughout their

existence, they can become ill, and fatal diseases can cause them financial distress. As a result, it is critical to accurately predict failure. This important phenomenon is solved by prediction models, which can vary. Furthermore, financial ratios are used as a potential predictor of failures. The study's emphasis is on the contemporary decision maker considering the results to recognise the influencing factors in order to establish the proper corrective and preventive initiatives to strengthen the CPSEs' profitability and liquidity position. The five factors (probability, liquidity solvency, managerial efficiency, and capital output ratio) were used to develop the model. The logistic regression results show that profitability, liquidity, solvency, and managerial efficiency all have a significant impact on failure and increase the risk of failure. The experimental results of logistic regression show 83.9 percent accuracy in predicting financial failure. This study raises the potential for regulatory and policy reforms, this may increase the possibility of the survival of the CPSEs. The Altman Z-score indicates that the financial health of the enterprise is very weak and soon to be bankrupt. Only four CPSEs are falling under gray zone and only Bharat Dynamics Ltd. (3.00) is in the safe zone. So it is now imperative for the policy makers, management and stakeholders to design and formulate strategies and policies to avoid failure and curb the effect of failure in the future. The results and the model discussed in this study will definitely enhance the chances of survival and better performance of the CPSEs. We argue that accurate prediction of CPSEs financial failure is critical from the standpoint of stakeholders in order to reduce the potential risk.

The models are primarily studied with the assistance of 27 CPSEs from the heavy, medium, and light manufacturing sectors. The models used in this study had a high level of accuracy in predicting the likelihood of failure. However, a large sample elaboration could improve the model's accuracy. According to the findings, a group of more quantifiable data, such as financial ratios, must be included in bankruptcy prediction, while qualitative metrics, such as symptoms of insolvency, and variables that affect financial failure, should be fully integrated for future research.

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