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DETECTION OF FINANCIAL DISTRESS IN THE INDIAN AUTOMOBILE INDUSTRY

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Abstract *India became the fourth largest automotive market in 2019, displacing Germany. By 2021, India is projected to overtake Japan as the third largest market in automobiles. The Indian automobile industry, which accounts for nearly 22% of the manufacturing industry, and contributes 7.1% to the country's GDP, faced problems related to fall in production and fall in sales in the domestic market, as well as slower growth in export. The Indian automobile industry provides 37 million employment directly and indirectly, and the performance of the industry is important for the overall economic recovery of the country. This study's objective is to evaluate the financial distress in the Indian automobile industry. The study used annual data of selected Indian automobile manufacturing firms for the fiscal year 2015-16 to 2019-20. The sample method used in the study is purposive sampling, with ten of the largest automobile companies listed on the Bombay Stock Exchange Ltd. (BSE), in terms of market capitalisation. The Altman, Grover, Springate, and Zmijewski models are applied to find distress scores results, which will confirm if there is any change in the financial performance of the companies. The financial performance measured over the study period has not significantly changed. In addition, comparing the results of the distress models shows that the distress level predicted for the selected automobile firms are significantly the same.*

Keywords: *Distress, Automobile, Altman, Grover, Springate, Zmijewski*

JEL Classification: *G10, G33*

INTRODUCTION

The Indian automotive industry is seeing a fundamental shift with regard to its sustainable value creation. The sector is crucial for the economy, as it accounts for 7.1% of the gross domestic product (GDP) of the country and its contribution is expected to increase to 12% as per the Automotive Mission Plan (AMP) 2016-26. By 2021, India is projected to emerge as the third largest passenger vehicle market in the world. The fundamentals of the automotive industry's growth factors remain intact and the industry is expected to see a rising demand pattern in the coming years as the economic climate improves and investments increase. The 'Make in India' initiative by the government has played an important role in raising the position of the country, and in the last three to four years, it has strengthened nine out of ten parameters for ease of doing business. Today, India is regarded as a desirable destination for low-cost development. It has been ranked 30th on the Global Manufacturing Index by the World Economic Forum, which quantifies countries' production capabilities. In this scenario, India's automotive industry (including component manufacturing) is expected to reach USD51.4-282.8 billion by 2026. There are a couple of key developments that are affecting the sector today, which are supposed to have a huge effect on its ability to achieve the AMP goals. The sector is also expected to create additional direct and indirect employment, in addition to the automation of different processes to achieve these objectives. In the recent past, the electric vehicle market has played a major role in triggering industry growth.

In any industry, the key to long-term survival is the soundness of the financial decisions taken by the firms. Generating positive ROI and increasing earnings per share, leading to escalated market value of shares, surely indicates a healthy firm. On the contrary, it is easy for a business, even a well-managed business, to experience a time of financial distress. A sudden, unforeseen decline in the overall economy could result in a significant drop in the revenues of a company. In the aftermath of the COVID-19 pandemic, several brick-and-mortar stores that had previously enjoyed a strong, steady income for years

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suddenly saw their sales drop to zero as a consequence of the quarantine and lockdown. Therefore, there can be multiple factors affecting the liquidity issues of the firm.

As per the SIAM report, the auto industry production in April-March 2020 against 30,914,874 in April-March 2019, registered a de-growth of (−) 14.73% over the same period last year. The production is impacted by domestic sales as well as exports. There was decline in auto sales across all the segments, be it passenger vehicles, commercial vehicles or two-wheelers. There is an exception in utility vehicle sales, but the sales increase is very marginal, at 0.48%. Certainly, the decline in industrial production and sales is attributed to the COVID pandemic, but the trend of decline in sales and production was experienced earlier as well. So, there is a need to explore the financial conditions of companies in the sector so that necessary actions can be taken by the stakeholders.

Financial distress is a term widely used in corporate finance that defines any situation where the financial state of a person or business leaves them unable to pay their bills, especially creditors' loan payments. Extreme, sustained financial distress will lead to bankruptcy, eventually. As a result, precise analytical tools are required to predict corporate bankruptcy among the companies in which investors are prepared to invest, along with the design of countermeasures (Antunes et al., 2017). The predictive analytics are early detection systems focused on an analysis of selected indicators that are capable of showing a danger to the financial health of a company. The models are built on the premise that it is possible to detect signs of potential issues that are typical of these businesses a few years before bankruptcy (Braunova & Jantosova, 2015).

They may recognise signs of possible future issues, which can help the company avoid severe repercussions for the business, if solved early (Daniela et al., 2016). This analysis helps the stakeholders predict the liquidity issues at an early stage, which can lead to taking preventive measures in time so that the loss of interest of the stakeholders could be saved. Of course, there are certain people that will be affected if the company goes bankrupt; the parties that have interests in the companies, such as investors and creditors (Adriana et al., 2012). A method or prediction model may be used to forecast the existence or absence of a company's possible bankruptcy, in order to mitigate the probability of bankruptcy. In terms of the best prediction models, multiple studies comparing the three models – the Altman Z-score model, Zmijewski model, and Springate model have different conclusions (Putra, Ivan Gumilar Sambas & Rahma Septiani, 2016).

LITERATURE REVIEW

A numerical measurement that is used to estimate the probability of a corporation going bankrupt in the next two years is the Z-score model by Altman (Altman Model, 1968). The model was developed to measure the financial stability of companies, by American finance professor Edward Altman, in 1968.

By using multiple balance sheet values and corporate profits, Altman's Z-score model is considered an efficient method of forecasting the state of financial distress of any company. At the time of the Great Depression, Altman's concept of creating a model for predicting bankruptcy began when corporations experienced a dramatic increase in incidences of default.

Avenhuis (2013) tested bankruptcy prediction models with statistical techniques and analysed the function of accounting ratios and tested all logit regression bankruptcy prediction models using Altman Z-score, Ohlson O-score, and Zmijewski X-score for 14 bankrupt and 326 non-bankrupt firms for the 2011-12 study period. The estimation sample covered all three methods, and the results demonstrated the highest precision of the Zmijewski X-score model. In order to boost the predictive ability, the author suggested re-estimating the coefficient of bankruptcy models with a particular and bigger sample.

Chadha (2016) analysed the financial results of 196 companies listed on the Kuwait Stock Exchange using the Zmijewski X-score and Altman Z-score models, for the period 2009 to 2014. The outcome of the Altman Z-score model showed that 25.94% of the companies were in distress, on average, and the Zmijewski X-score model could not be justified because of inconclusive results and the absence of Kuwaiti bankruptcy law.

Erni and Sofyan (2020) analysed the bankruptcy of retail trading companies listed on the Indonesian Stock Exchange. Altman score and Springate score results revealed that out of six selected companies, only three were in good financial condition. Altman score also categorised three companies in the grey zone.

Salim and Sudiono (2017) analysed the probability of bankruptcy of 19 coal mining companies listed on the Indonesian Stock Exchange using Altman Z-score, Springate S-score, and Zmijewski X-score models for the period 2011 to 2014. Compared to the Altman Z-score and Springate S-score models, the Zmijewski model was found to be the most reliable predictive model.

Hutabarat (2017), using Springate and Zmijewski models, examined the financial distress of ten listed companies in the banking sector on the Indonesian Stock Exchange. The outcome revealed that all ten firms were in financial distress.

Nandi, Sengupta and Dutta (2019) conducted a study on 12 OMCs in India to evaluate the distress level and predict bankruptcy in the petroleum sector. Altman Z-score revealed that 75% of the selected companies were in good financial condition.

Primassari (2017) used the sample according to the Altman Z-score during model production, by adding 13 financial ratios. He used a selection of 70 firms – 35 bankrupt and 35 non-bankrupt firms. He considered the duration of data between 1982 and 1996. The Grover model literature review shows the following facts: a report on Grameen Bank in Bangladesh using the same models was conducted by Qamruzzaman & Jianguo (December, 2016). Its analysis concludes that conflicting predictions are given by the G-score. Grover was discovered (Primassari, 2017) as the least precise model. The majority of Grover model reviews show negative opinions about its predictions. This suggests that this model needs to be revised.

Sajjan's (2016) study aimed at presenting a theoretical foundation, and compared the results of investigating two models – Zavgren and Springate. Results indicate that the adjusted Springate model was more efficient than other models in the bankruptcy year.

Sinarti and Sembiring (2015) used Altman Z-score, Springate S-score, and Zmijewski X-score models to find out singleness among all three models; this research paper analysed the bankruptcy of 11 listed manufacturing companies. To prove the hypothesis, linear regression and t-test were used. The findings showed that the estimation of Altman Z-score and Springate S-score models were not substantially different, but there is a substantial difference between all three models.

Soon et al. (2014) used Altman's financial distress model to predict the financial hardship of 28 companies listed under the trading services sector at the Malaysian Stock Exchange for the period 2003-2009, and concluded that Altman's score can be used to differentiate between failure and non-failure companies, and that it is useful for investors to predict the financial failure of companies.

The Springate model (1978), created by Gordon Springate in 1978, selected four out of 19 common financial ratios to assess the probability of failure of firms. In order to find scores for each particular company, this model often uses step-wise discriminant analysis.

Originally, Springate used this model for 40 companies with an accuracy rate of 92.5%. In later tests carried out by other academic researchers, a 50-company test (with average assets of 2.5 million) showed an accuracy rate of 88%, and a 24-company test (with average assets of 63.4 million) showed an accuracy rate of 83%.

Verlkar and Kamat (2019) evaluated the Grover score, Springate score, and Zmijewski X-score prediction effectiveness on the Indian banking sector by using all the listed banks in BSE/NSE. The results were not significant and also showed that 21 banks were safe and 18 banks were in the grey zone and near bankruptcy category.

RESEARCH GAP

From a review of the recent past literature, the gaps identified were absence of research study on evaluating the distress level of the automobile sector in India in the last five years. In addition, the earlier distress study conducted in the selected companies or sectors did not assess the distress level corresponding to the time period of study.

OBJECTIVES OF THE STUDY

- To predict the financial distress level of selected Indian automobile companies.
- To analyse the change in financial health of selected Indian automobile companies.

RESEARCH METHODOLOGY

The study is a descriptive study, which uses the financial variables and ratios to estimate the distress level of the selected companies over the study period.

The study takes into consideration the automobile industry of India, with top ten automobile companies listed under BSE. In order to study the financial distress of the concerned companies, Altman score, Grover score, and Springate scores are calculated to predict the early signs of financial distress, if any, with these companies, which can be cured over time.

Sampling

Sampling is a non-probability technique. Purposive sampling technique is adopted to select automobile companies for the study sample. The study is carried out on ten of the largest automobile companies on the basis of market capitalisation as of March 2020.

Rank	Companies	Market Cap (Rs. in Crores)
1	Tata Motors	2228147.92
2	Maruti Suzuki	202729.24
3	M&M	82844.279
4	Bajaj Auto	80683.721
5	Eicher Motors	54160.0186
6	Hero Motors	51957.837
7	Ashok Leyland	25338.257
8	TVS Motors	22581.685
9	Escorts Ltd.	8642.987
10	Force Motors	1978.987

Variables of Study

To analyse the financial performance and estimate the distress level, the following variables and parameters are estimated:

- A = working capital/total assets
- B = retained earnings/total assets
- C = earnings before interest and tax/total assets
- D = market value of equity/total liabilities
- E = sales/total assets
- F = return on assets (ROA)
- G = net profit before taxes to current liabilities
- H = total liabilities/total assets
- I = current assets/current liabilities

Data Analysis Techniques

Distress Score Model

Altman Score

Altman Z-score is an upgradation on statistical Z-score, as it includes financial variables. It was developed by Edward Altman in 1967. The Z-score uses five key financial ratios and is expressed as follows:

$$\text{Z-Score} = 1.2A + 1.4B + 3.3C + 0.6D + 1.0E$$

Where:

- A = working capital/total assets
- B = retained earnings/total assets
- C = earnings before interest and tax/total assets
- D = market value of equity/total liabilities
- E = sales/total assets

A score below 1.8 means it is likely that the company is headed for bankruptcy, while companies with scores above three are not likely to go bankrupt. Investors can use Altman Z-scores to determine whether they should buy or sell a stock if they are concerned about the company's underlying financial strength. Investors may consider purchasing a stock if its Altman Z-Score value is closer to three, and consider selling or shorting a stock if the value is closer to 1.8.

Grover Score

The Grover model is created by designing and reassessing the Altman Z-score model. Jeffrey S. Grover used samples according to the Altman Z-score model in 1968 by adding 13 new financial ratios. The samples used were 70 companies, 35 of which experienced bankruptcy and the remaining 35 did not, between 1982 and 1996. Grover (2001), in Prihanthini (2013), involves the following equation:

$$G = 1.65A + 3.404C - 0.016F + 0.057$$

Where:

A is working capital by total assets

C is net profit before interest and tax/total assets

F is return on assets (ROA).

The Grover model categorised firms as bankrupt if the scores were less than or equal to −0.02 ($Z < -0.02$), while value for companies categorised as not bankrupt was 0.01 ($Z > 0.01$) (Prihanthini & Sari, 2013).

Springate Model

The Springate model was the first model to be introduced by Gordon LV Springate (1978). Basically, this model is a revolution of the Altman model, developed by Multiple Discriminant Analysis (MDA). The Springate model development process initially used 19 financial ratios that have been frequently used. However, after testing, Springate finally chose four financial ratios to be used to determine whether the company is healthy or potentially insolvent.

The Springate model equation proposed by Springate is:

$$S = 1.03A + 3.07C + 0.66G + 0.4E$$

Where:

A = working capital to total assets

C = net profit before interest and taxes to total assets

G = net profit before taxes to current liabilities

E = sales to total assets

Zmijewski X-Score

The Zmijewski X-Score is used to analyse the distress of companies using probit models. An X-score above 0.5 is considered a financially healthy firm.

$$X = -4.336 - 4.513*F + 5.679*H + 0.004*I$$

Where:

F = net income/total assets

H = total liabilities/total assets

I = current assets/current liabilities

Distress Model	Equation	Categories	Inferences
Altman Score (1968)	Z = 1.2A + 1.4B + 3.3C + 0.6D + 1.0E	Z < 1.81 1.81< Z < 2.99 Z > 2.99	Distress/ Near Bankruptcy Grey Zone / Stable Safe
Grover Score (1968, 2001)	G = 1.65A + 3.404C – 0.016F + 0.057	G < – 0.02 G > 0.01	Distress/ Near Bankruptcy Safe
Springate Model (1978)	S = 1.03A + 3.07C + 0.66G + 0.4E	S < 0.862 S > 0.862	Distress/ Near Bankruptcy Healthy
Zmijewski X-Score (1984)	X = −4.336 − 4.513*F + 5.679*H + 0.004*I	X > 0.5 X < 0.5	Solvent Distress

Hypothesis Testing

Jarque-Bera Test

The normality of the distress score over the period of study is calculated to assess the significant change in financial health of the firm (Chouhan, Vineet, Chandra, et al., 2014). The Jarque-Bera test for normality of distribution in a small sample is given by:

$$JB = \frac{n}{6}\left(S^2 + \frac{1}{4}(K-3)^2\right)$$

Where, n is number of observations in sample, S is skewness, and K is kurtosis.

H_{01}: There is no significant change in the financial performance level of the selected companies.

H_{a1}: There is significant change in the financial performance level of the selected companies.

Analysis of Variance (ANOVA)

One-way ANOVA is an extension of the t-test, to compare mean between groups. If the group are more than two, then one-way ANOVA is used. One-way ANOVA tests if the groups' mean are significantly different from each other, based on the one identified factor, by applying the F-test used to check the variance.

	Sum of Squares	df	Mean Square	F
Treatment	SSR	dfr	MSR	MSR/ MSE
Error	SSE	dfe	MSE	
Total	SST	dfT		

Where:

SSR and MSR are sum of square and mean sum of square of regression.

SSE and MSE are sum of square and mean sum of square of error.

df stands for degrees of freedom of model (r) and error (e).

H_{02}: *There is no significant difference in mean scores among the distress models.*

H_{a2}: *There is significant difference in mean scores among the distress models.*

DATA ANALYSIS AND FINDINGS

Financial performance

The analysis of the study used the three scores – Altman score, Springate Score, and Grover Score – to assess the financial distress of the top ten listed companies under BSE in the automobile sector. Table 1 shows the calculated values of the variables required under the model.

Table 1: Financial Performance of 10 Companies

Companies	A	B	C	D	E	F	G	H	I
Tata Motors	−0.1562	0.3393	0.003	54.831	0.7727	−0.0286	−0.0255	0.6463	0.589
MSZK	−0.0728	0.7241	0.1698	12.675	1.3658	0.1222	0.7010	0.2731	0.7013
M&M	0.0690	0.6442	0.1131	7.7442	1.0618	0.0781	0.2973	0.345	1.2735
Bajaj Auto	0.1609	0.7918	0.2693	18.386	1.1643	0.1939	0.2692	0.1950	1.9738
Eicher	0.1311	0.7110	0.3650	31.453	1.2802	0.2519	1.4350	0.2847	1.7125
Hero	0.2213	0.7007	0.3034	12.526	1.9756	0.2180	1.1589	0.2964	1.8746
Ashok Leyland	−0.0363	1.0181	0.2341	3.2837	3.448	0.1559	0.1965	1.377	0.922
TVS Motors	−0.1219	0.3912	0.1218	5.2152	2.1232	0.0858	0.2308	0.6018	0.7520
Escorts	0.0948	0.5676	0.1055	3.9638	1.1390	0.0683	0.2663	0.4030	1.2698
Force	0.1532	0.6587	0.0768	3.9210	1.2970	0.0553	0.2506	0.3363	1.532

Source: Computed by Authors, Averaged values for study period.

From Table 1, we have tried to analyse all companies' financial performance based on financial ration represented from column A to I. In each column, the maximum value is highlighted in yellow and the minimum value in red. Tata Motors has the minimum average sales/total assets, return on assets (ROA), and net profit before taxes to current liabilities, but has the maximum retained earnings/total assets and earnings before interest and tax/total assets.

Ashok Leyland has the minimum value in working capital/total assets, retained earnings/total assets, and market value of equity/total liabilities, but has the maximum in sales/total assets.

Similarly, Eicher Motors has the maximum value in earnings before interest and tax/total assets, return on assets (ROA), and net profit before taxes to current liabilities. Further, Hero Motors has the maximum value in working capital/total assets and total liabilities/total asset.

Lastly, Bajaj Auto has the maximum in total liabilities/total assets and the minimum value in current assets/current liabilities.

If we see the financial ratios selected for the study, the variable represented by B to G are profitability and revenue ratio, which are favourable if they are higher. However, other ratios that represent leverage of the companies need to trade-off with their impact on profitability and risk.

Altman Z-Score

Table 2: Altman Z-Score

	2020	2019	2018	2017	2016	Healthy>3
Tata Motors	30.221	36.161	47.652	32.498	23.321	Healthy
M&M	5.238	5.075	5.661	9.815	9.541	Healthy
MSZK	11.169	10.106	12.161	10.295	8.561	Healthy
Hero	10.410	10.620	12.978	12.676	12.014	Healthy
Bajaj Auto	13.261	11.727	14.395	16.282	16.265	Healthy
Ashok Leyland	6.815	7.401	7.846	7.645	8.157	Healthy
Escorts	5.442	5.354	6.097	4.391	2.586	Healthy
TVS Motors	4.748	5.674	7.319	6.437	6.100	Healthy
Eicher	17.318	17.293	21.975	28.334	27.627	Healthy
Force	3.042	3.970	6.061	6.402	5.570	Healthy

Source: Computed by Authors, Averaged values for study period.

The Z-score, as per the Altman Model of all the companies (Table 2) is beyond three, indicating the healthy financial status of the ten automobile companies under study. Though the Z-score for Escorts for 2016 is less than three, the score improved over time and was beyond five in 2020. In addition, the Z-score for Force Motors was around six during 2015-16 to 2017-18, but suddenly fell to 3.97 in 2018-19 and then to 3.04 in 2019-20. Force Motors need to concentrate on liquidity issues in order to avoid further decline in the Z-scores.

Springate Score

Table 3: Springate Score

	2020	2019	2018	2017	2016	Healthy>0.862
Tata Motors	−0.487	0.525	0.263	0.106	0.303	Near Bankruptcy
M&M	0.717	1.071	1.099	1.169	1.140	Healthy
MSZK	1.177	1.501	1.468	1.604	1.527	Healthy
Hero	2.355	2.658	2.807	2.793	2.960	Healthy
Bajaj Auto	1.559	1.428	1.549	1.698	1.946	Healthy
Ashok Leyland	1.475	2.514	2.400	2.276	2.286	Healthy
Escorts	1.269	1.372	1.168	0.871	0.585	Healthy
TVS Motors	0.937	1.286	1.234	1.317	1.476	Healthy
Eicher	2.347	2.733	2.355	2.826	3.314	Healthy
Force	0.543	1.090	1.180	1.180	1.396	Healthy

Source: Computed by Authors, Averaged values for study period.

The Springate model scores (Table 3) for Tata Motors indicates the financial distress of the company. The score for 2019-20 for Mahindra & Mahindra is also less than 0.862, which indicates financial distress in that year, though the scores for the other years for the company are within the acceptable limits, defining its healthy financial condition. In the year 2015-16, Escorts' Springate score was 0.58, indicating financial distress; however, over time the scores improved for the company. In the year 2019-20, Force Motors had a low Springate score of 0.54, indicating the financial distress of the company. As per the model, it is Tata Motors, Mahindra & Mahindra, and Force Motors that have low scores in 2019-20, indicating financial distress.

Grover Score

Table 4: Grover Score

	2020	2019	2018	2017	2016	
Tata Motors	−0.5442	0.0277	−0.1546	−0.2338	−0.0371	Near Bankruptcy
M&M	0.4104	0.5884	0.6113	0.5941	0.5675	Healthy
MSZK	0.3716	0.5784	0.4966	0.5789	0.5401	Healthy
Hero	1.2678	1.3952	1.5652	1.5112	1.5179	Healthy
Bajaj Auto	1.1144	1.0201	1.2358	1.4167	1.3934	Healthy
Ashok Leyland	0.1935	1.0660	1.0510	0.8475	0.7991	Healthy
Escorts	0.8272	0.8365	0.6640	0.3550	0.1748	Healthy
TVS Motors	0.1415	0.3045	0.2229	0.2980	0.3781	Healthy
Eicher	1.5377	1.5988	1.2811	1.4170	1.7245	Healthy
Force	0.2005	0.5592	0.6231	0.6772	0.7917	Healthy

Source: Computed by Authors, Averaged values for study period.

The G-score as per the Grover model for Tata Motors (Table 4) indicates values below −0.02 from 2015-16 to 2019-20, except for the year 2018-19. Grover G-score for Tata Motors reveals the near bankruptcy situation in 2017-18 and 2015-16, and a grey area in 2019-20 and 2016-17. Grover model G-score for all other companies under study for the given time period reveals scores beyond 0.01, indicating financial soundness of the considered companies.

Zmijewski X-Score

Table 5: Zmijewski X-Score

	2020	2019	2018	2017	2016	Solvent < 0.5
Tata Motors	−5.4637	−9.2048	−8.8626	−8.2456	−8.0513	Solvent
M&M	−2.6463	−2.7493	−2.6949	−2.8691	−2.6468	Solvent
MSZK	−3.4592	−3.3552	−3.2362	−3.3385	−3.2779	Solvent
Hero	−3.8050	−3.6540	−3.6386	−3.5947	−3.4527	Solvent
Bajaj Auto	−4.1476	−3.9392	−3.9735	−4.1227	−4.2958	Solvent
Ashok Leyland	5.0233	1.4366	1.8131	2.2635	3.4036	Insolvent
Escorts	−2.7833	−2.5246	−2.4056	−2.0778	−1.9610	Solvent
TVS Motors	−1.1346	−1.2865	−1.3492	−1.3968	−1.3454	Solvent
Eicher	−3.8979	−3.8967	−3.5582	−3.9449	−3.9453	Solvent
Force	−2.3149	−2.7592	−2.9690	−2.6006	−2.6684	Solvent

Source: Computed by Authors, Averaged values for study period.

The X-score, as per the Zmijewski model, for Ashok Leyland (Table 5) indicates values below −0.5 from 2015-16 to 2019-20. Zmijewski score for all other companies indicate that they are solvent. The result is different from other distress scores (i.e. Altman, Grover & Springate). For the same, we have first tried to compare uniformity of score for a particular company over the study period, and then the scores among the distress model using ANOVA.

Jarque-Bera Test

To test the normality of the data, the Jarque-Bera test has been applied. The results are shown in Table 6.

Table 6: Jarque-Bera Test

Companies	Altman	Springate	Grover	Zmijewski
Tata Motors	0.857	0.684	0.737	0.5811
M&M	0.667	0.47	0.459	0.7068
MSZK	0.908	0.581	0.648	0.8549
Hero Motors	0.728	0.772	0.734	0.9577
Bajaj Auto	0.797	0.765	0.772	0.835
Ashok Leyland	0.845	0.501	0.6	0.7371
Escorts	0.711	0.762	0.739	0.8184
TVS Motors	0.922	0.803	0.86	0.6531
Eicher	0.727	0.806	0.867	0.4301
Force	0.739	0.647	0.674	0.9193

Source: Computed by Authors, Averaged values for study period.

In Table 6, we have all three estimated distress parameters, viz., Altman score, Springate score, and Grover score, and all scores are normally distributed, as all the p-values are more than 0.05. Thus, we can infer that we fail to reject H_0; therefore, the sample data are not significantly different from each other over the years.

Comparison of Distress Scores between Models

Table 7: One-Way ANOVA

SUMMARY				
Groups	*Count*	*Sum*	*Average*	*Variance*
ALTMAN	10	7.901	0.7901	0.007855
SPRINGER	10	6.791	0.6791	0.015606
GROVER	10	7.09	0.709	0.014819
ZMIJEWSKI	10	7.4935	0.74935	0.026332

Source of Variation	SS	df	MS	F	P-Value	F Crit.
Between Groups	0.07004	3	0.023347	1.445333	0.245737	2.866266
Within Groups	0.581512	36	0.016153			

Source: Computed by Authors, Averaged values for study period.

In Table 7, since the p-value is greater than 0.05, we fail to reject the null hypothesis and can infer that the results are not significantly different in analysing the financial performance of the companies.

CONCLUSION

The distress scores of the selected companies support the results estimated by various financial performance ratios. The Altman score has rated all the companies as healthy companies, across the study period. However, the Grover score rated Tata Motors as near bankruptcy and in the grey zone in 2 years each out of the five-year study period. In addition, Springate score rated Tata Motors as near bankruptcy throughout the study period. M&M Ltd., Escorts Ltd., and Force Motors Ltd. were also rated near bankruptcy in the years 2017 and 2020, respectively, according to the Springate scores.

To conclude the analysis, the average of estimated distress scores of selected companies using Altman score, Springate score, and Grover score presented the same results for all the companies, except Tata Motors. Tata Motors was identified as near bankruptcy by Springate score and Grover score, and healthy by Altman score.

The results of the financial performance measured by various scores have presented similar results for 6 out of 10 companies. Surely the consistency between the results presented by the score can be evaluated in further studies, as it is not under the scope of the current study.

The automobile industry in recent years, especially 2018-19, saw a slowdown in sales in the domestic market, as well as in exports. The financial performance evaluated by all the scores accepts that there is no significant change over the study period. Nevertheless, companies like Tata Motors consistently in near bankruptcy, and M&M and Force Motors identified as near bankruptcy in recent years, is not a good indicator, as their market share is significant in all segments of automobiles and its ancillaries in India. The result is similar according to the 4 different distress models for the selected automobile companies.

SCOPE FOR FURTHER RESEARCH

The current study evaluated the financial performance and distress status of automobile manufacturers in India. A similar study can be conducted on other sectors experiencing decline in sales or profit, so that the companies can be identified and stakeholders can take necessary precautionary steps. In addition, the consistency between the results of different distress scores by using appropriate statistical techniques can be evaluated.

The model used in the study has used only financial variables, which are internal to the firm. So the model does not include important macroeconomic variables, like GDP growth rate, interest rate, inflation, foreign exchange rate, and so on. All the above points can be adopted for further research.

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