IMPACT: International Journal of Research in
Business Management (IMPACT: IJRBM)
ISSN(P): 2347-4572; ISSN(E): 2321-886X
Vol. 4, Issue 12, Dec 2016, 9-24

DISCRIMINATORY POWER OF SELECTED RATIOS IN DEFINING STOCK MARKET PERFORMANCE OF AUTOMOBILE COMPANIES IN INDIA

ROSY DHINGRA[1] & KAPIL DEV[2]

[1]Research Scholar, Department of Management Studies

Punjab Technical University, Kapurthala, Punjab, India

[2]Assistant Professor, GGDSD College, Chandigarh, India

ABSTRACT

The main focus of the paper is to investigate the relationship between financial ratios and stock returns and to find the ratio(s) which can discriminate between outperformers and underperformers in stock market. Multiple discriminant analysis models with Wilks' Lambda were used on fourteen selected companies from April 1, 2004 to March 31, 2016. Market capitalization was the basis for this selection. For this a basic model was developed to identify the potential Good stock market performer and the Poor stock market performer, based on the Predictor variable viz. Eight ratios which were identified by the Discriminant Analysis. The classification summary shows that a good number of original Groups were correctly classified in to "Good" performer and "Poor" performer. This indicates a very good predictive capacity of the selected ratios. Also it has been concluded that financial variables viz. financial ratios have impact on the Capital Structure of the Automobile companies In India. The Market cap/Net Operating Revenue, Current ratio are the important set of ratio, having impact on financial performance of the companies. Revenue from operations/share, Asset turnover Ratio, Cash earnings Retention Ratio, PBDIT/share having moderate impact on financial performance of companies and Quick ratio and EV/Net operating Revenue are the set of ratios, having less impact on financial performance of companies.

KEYWORDS: Ratio Analysis, Automobile Industry, Multiple Discriminant Analysis, Average Market Stock Returns

INTRODUCTION

The Indian automobile industry seems to come a long way since the first car that was manufactured in Mumbai in 1898. The automobile sector today is one of the key sectors of the country contributing majorly to the economy of India. It directly and indirectly provides employment to over 10 million people in the country. The Indian auto industry is one of the largest in the world. The industry accounts for 7.1 per cent of the country's Gross Domestic Product (GDP). As of FY 2014-15, around 31 per cent of small cars sold globally are manufactured in India. Also the Indian automobile industry has a well established name globally being the second largest two wheeler market in the world, fourth largest commercial vehicle market in the world, and eleventh largest passenger car market in the world and expected to become the third largest automobile market in the world only behind USA and China. As Automobile Industry plays a crucial role in driving economy likewise capital structure plays an important role in driving financing of automobile industry. The relative proportion of various sources of funds used in a business is termed as financial structure. Capital structure is a part of the financial structure and refers to the proportion of the various long-term sources of financing. It is concerned with making the array of the sources of the funds in a proper manner, which is in relative magnitude and proportion.

But the research question is that ‘How do firms choose their capital structures’. In answer to this question, Prof. Stewart C. Myers, then President of American Finance Association in 1984 said that “we don’t know”. Many researchers have been conducted on corporate financing after the approaches of Modigliani and Miller, but it has been observed that there is lack of consensus on the basic issue of financing. In practice there is no optimum capital structure exists, finance managers use different combinations of debt and equity.

Consequently it is being increasingly realized that the company should plan its capital structure to maximize the use of funds and to be able to adapt more easily to the varying conditions. Capital structure decisions have been the most significant decisions to be taken by the financial experts in a corporate sector organization, since it carry a crucial impact on the overall cost of capital in terms of weighted average and the resultant market value of the shares. There have been various schools of thoughts on the relevance of capital structure to a firm’s performance. However, there is still no unifying theory of capital structure even after decades of serious research, which leaves the topic open for further research. The choice of capital structure for firms is one of the most fundamental premises of the financial framework of a corporate entity. The method by which public corporations finance their assets sets up their ownership structure and influence whether their corporate governance is of high standard. Also, there are various theories of capital structure with the different viewpoints. So, practical relevance of the theories need to be studied.

This paper tends to find out the discriminatory power of the financial ratios on stock market performance of selected Indian automobile companies listed with National Stock Exchange and test a range of hypotheses to analyse and compare the performance with the help of financial variables and multiple discriminate analyses.

REVIEW OF LITERATURE

Theoretical and empirical research suggests that financial planner should plan optimal capital structure. In practice, financial management literature does not provide specified methodology for designing a firm’s optimal capital structure.

Andreas Charitou (2004), examined the incremental information content of operating cash flows in predicting financial distress and accordingly build up consistent failure prediction models for UK public industrial firms using Neural networks and logit methodology of fifty-one matched pairs of failed and non-failed UK public industrial firms over the period 1988–97. The empirical results signify that an economical model that includes three financial variables of cash flow, profitability and financial leverage variable that capitulated an overall correct classification accuracy of 83% one year prior to the failure.

Barbro Back, Finland Turku, Laitinen Teija, Wezel Michiel van (1996), In this study an attempt is made by Choosing Bankruptcy Predictors Using Discriminant Analysis, Logit Analysis, and Genetic Algorithms. The aim is to study if these essential differences between the methods (1) affect the empirical selection of independent variables to the model and (2) lead to significant differences in failure prediction accuracy.

Chen & Shimerda (1981) claimed that there are too many (41ratios) financial ratios to be helpful in evaluating the financial performance and financial condition of a company. **Taffler (1983)** claimed there are only four out of eighty potential useful ratios in evaluating the financial performance and financial condition of a company. **Koh & Killough (1986)** claimed it is not necessitated to have a huge number of ratios to predict business failures but desirable is a set of dominant ratios derived from a larger set of correlated ratios. However **Hossari &Rahman (2005)** found commonly used 48 ratios in the past literatures.

Dr. Bhunia Amalendu, Mrs. Sarkar Ruchira 2011), conducted a Study of Financial Distress based on MDA. A total of sixty-four private sector pharmaceutical companies were analyzed with sixteen financial ratios using multiple discriminant analysis. A strong discriminant function was constructed with seven ratios found to be significant in discriminating power and the classification results showed high predictive accuracy rates of between 86% and 96% for each of the five years prior to actual failure. This study also indicated that even with more advanced statistical tools more popularly used recently, MDA is still a very reliable and potent statistical tool.

Fook Yap-Ben Chin, Fie Yong- David Gun-, Ching Poon-Wai (2010), conducted research on how well do financial ratios and multiple discriminant analysis predicts company failures in Malaysia. A total of 64 companies were analyzed with 16 financial ratios using multiple discriminant analysis. A strong discriminant function was constructed with seven ratios found to be significant in discriminating power and the classification results showed high predictive accuracy rates of between 88% to 94% for each of the five years prior to actual failure. This study also indicated that even with more advanced statistical tools more popularly used recently, MDA is still a very reliable and potent statistical tool.

Green (1978), stated that financial ratios have long been regarded as barometers of corporate health, being used for reporting liquidity, leverage, activity and profitability and that an investor may use financial ratios to appraise a company’s performance and its future prospect of success.

Hu and Ansell (2005) constructed retail financial distress prediction models based on five key variables with good classification properties using five credit scoring techniques—Naïve Bayes, Logistic Regression, Recursive Partitioning, Artificial Neural Network, and Sequential Minimal Optimization (SMO) considering a sample of 491 healthy firms and 68 distressed retail firms for the period from 2000 to 2004. An international comparison study of three retail market models for USA, Europe and Japan illustrates that the average accuracy rates are above 86.5% and the average AUROC values are above 0.79. More or less all market models exhibit the best discriminating ability one year prior to financial distress. The US market model executes comparatively better than European and Japanese models five years before financial distress.

SIGNIFICANCE OF STUDY

It has been realized there are less number of researchers on the stock market performance of automobile industry of India based on financial ratios but there is a research gap in this area. This will help management, shareholders, moneylenders, employees, government and citizens of the country who are also interested in knowing the affairs of the Company. Moreover, a critical appraisal/ evaluation is needed to satisfy government shareholders investors that the company is utilizing its financial resources very well.

RESEARCH OBJECTIVE

- To analyse and compare the performances of the automobile companies in India listed on National Stock exchange as per their market capitalization.
- To find the most important set of ratios, having impact on stock market performance of the companies.

- To find the discriminatory power of these sets of Ratios.

Research Question

The main focus of the paper is to investigate the relationship between financial ratios and stock returns. The idea behind this exercise is to explore if some of the ratios of financial performance of any firm has any discriminatory power to explain the difference between good and poor performing companies.

Hypotheses

H_0: None of the financial ratios has discriminatory power to differentiate between good and poor stock market performance of selected automobile companies in India.

$H_{1:}$ At least one of the financial ratios has discriminatory power to differentiate between good and poor stock market performance of selected automobile companies in India.

RESEARCH METHODOLOGY

Period of Study

The present study has been time specific for its scope. It covers the period of Twelve years ranging from April 1, 2004 to March 31, 2016. Annual Stock Prices for the selected companies for this specific period have been used.

Data Collection

This study is secondary data based research, coming up with conclusions which are capable of being verified by observation or experiment. It will utilize secondary data through published annual reports listed on National Securities Exchange companies' website and money control website and. CMIE PROWESS database will be used to collect financial information. To supplement the data so collected from annual reports and accounts, other publications like newspaper, monthly journals and magazines etc. will also be used.

Sample Size

To begin with the study, a sample of fourteen automobile companies listed on national stock exchange will be selected. Market capitalization would be the basis for this selection. Sample will be selected keeping in mind only those companies which remained in list of NSE for at least three years from 2009-10 to 2011-12. This sample includes Private companies.

Tools of Analysis

For the purpose of the analysis various accounting and statistical techniques have been used. Multiple discriminate analyses is used and Average Market stock returns are used to classify the companies into "Good" and "Poor" stock market performance. Financial variables in the form of Ratios are to be used to check their impact on the financial performance of the companies.

DISCRIMINANT ANALYSIS

Discriminant analysis is a technique for analyzing data when the criterion or dependent variable is categorical and predictor or independent variables are interval in nature. Discriminant function analysis is used to determine which continuous variables discriminate between two or more naturally occurring groups. Discriminant analysis is a classification problem, where two or more groups or clusters or populations are known *a priori* and one or more new observations are classified into one of the known populations based on the measured characteristics. The original dichotomous discriminant analysis was developed by Sir Ronald Fisher in 1936. It is different from an ANOVA or MANOVA, which is used to predict one (ANOVA) or multiple (MANOVA) continuous dependent variables by one or more independent categorical variables. Discriminant function analysis is useful in determining whether a set of variables is effective in predicting category membership. The Discriminant Function, Multiple discriminant analysis (MDA) is also termed Discriminant Factor Analysis and Canonical Discriminant Analysis. It adopts a perspective similar to Principal Components Analysis, but PCA and MDA are mathematically different in what they are maximizing. MDA maximizes the difference between values of the dependent, whereas PCA maximizes the variance in all the variables accounted for by the factor. In simple terms, discriminant function analysis is classification - the act of distributing things into groups, classes or categories of the same type.

Discriminant analysis technique, researcher may classify individuals or objects into one of two or more mutually exclusive and exhaustive groups on the basis of a set of independent variables and a nominal dependent variable. Discriminant analysis works by creating one or more linear combinations of predictors, creating a new latent variable for each function. These functions are called discriminant functions. The discriminant analysis is considered an appropriate technique when the single dependent variable happens to be non-metric and is to be classified an appropriate technique when the single dependent variable happens to be non-metric and is to be classified into two or more groups, depending upon its relationship with several independent variables which all happen to be metric. The objective in discriminant analysis happens to be to predict an objects likelihood of belonging to a particular group based on several independent variables. In this case we classify the dependent variable in more than two groups then we use the name multiple discriminant analysis. This paper will explain the performance of automobile companies in India. Using multiple discriminant analysis the companies are divided into two groups that is good and poor stock market performance companies. Under that discriminant analysis calculating discriminate score and cutoff rate.

Formula for using multiple discriminate analysis:

Z= a+v1x1+v2x2+…..vnxn

'a' is the constant term, which is in the following table viz 'Canonical Discriminant Function Coefficient'.

v1v2= are the corresponding unstandarised discriminant function coefficient

x1 x2=are the independent variables

Z=Discriminant Score

In that paper reveals that with identification of a set of variables to be used for constructing a model to identify "good stock market performers" and "poor stock market performers" among the fourteen automobile companies in India. Ratios are used as variables, to identify the "good" and "poor" performers, in the process of identifying discriminant variables and their discriminant co-efficient. Financial ratios individually do not contribute much, to identify the performance of automobile Industry as a whole. Hence ratio analysis, a financial tool and discriminant analysis, a statistical tool are combined for construction of a model to analyze the performance of the automobile Industry in India. These ratios are calculated from financial statements viz... Balance sheet and profits and loss accounts of automobile companies for fourteen years from April 1, 2004 to March 31, 2016. Based on these, ratios have been calculated for every year separately and used along with coefficients to calculate Z-score.

PROCESS OF IDENTIFICATION OF GOOD STOCK MARKET PERFORMER AND POOR STOCK MARKET PERFORMER OF AUTOMOBILE COMPANIES IN INDIA

The process of identification has been done through a simple test. As the sample consists of the returns on holding the stock for a year and the return on the stock is calculated on the unadjusted price of a particular stock.

Market adjusted return is calculated on the excess of stock specific return on the benchmark index BSE Sensex in order to nullify the effect of uncontrollable market factors on the stock price.

- If the Average Market adjusted return for a sample is above 10% of benchmark index, then the sample is said to be a part of categorical group ‘Good’.
- If the Average Market adjusted return for a sample is below 10% of benchmark index, then the sample is said to be a part of the categorical group ‘Poor’.

All the selected automobile companies have been classified into two groups, that is ‘One’ and ‘Two’, One’ that is ‘Poor’ stock market performers and ’Two’ that is ‘Good’ stock market performing Companies whose Average Market adjustment return is above below 10% is considered under ‘poor’ Group that is ‘One’ and whose Average market return is above 10% is Considered to be ‘Good’’ Group that is ‘Two’ There by each company are gets weights of either 1 or 2 for each ratio depending upon their average market returns. Then weights are added.

Table1: Classification of Automobile Companies According to the Weights

S. No	Company	Average Market Stock Return	Performance Group
1	Ashok Ley.	0.0908	1
2	Atul Autos	0.2383	2
3	Bajaj Autos	0.051	1
4	Eicher Motors	0.355	2
5	Force Motors	0.1775	2
6	Hero Motocorp	0.15	2
7	Hind. Motors	-0.0742	1
8	Honda Motocorp	-0.1625	1
9	M & M	0.091	1
10	Maruti	0.18	2
11	Sundaram Clay	0.1	1
12	Tata Motors	-0.0125	1
13	TVS	0.0825	1
14	VST Tillers	0.2883	2

Wilks’ Lambda

Wilks’ lambda performs, in the multivariate setting, with a combination of dependent variables, the same role as the F-test performs in one-way analysis of variance. Wilks’ lambda is a direct measure of the proportion of variance in the combination of dependent variables that is unaccounted for by the independent variable (the grouping variable or factor). If a large proportion of the variance is accounted for by the independent variable then it suggests that there is an effect from the grouping variable and that they have different mean values. Wilks' lambda statistic can be transformed (mathematically adjusted) to a statistic which has approximately an F distribution. This makes it easier to calculate the P-value. Often authors will present the F-value and degrees of freedom, as in the above paper, rather than giving the actual value of Wilks' lambda. There are a number of alternative statistics that can be calculated to perform a similar task to that of Wilks' lambda.

Table 2: Discriminant Stepwise Statistics Variables in the Analysis

Step	Variables	Tolerance	Wilks' lambda
1.	Current Ratio (X)	1.000	
2.	Current Ratio (X)	1.000	.855
	Revenue from Operations/Share (Rs.)	1.000	.808
3.	Current Ratio (X)	.124	.771
	Revenue from Operations/Share (Rs.)	.888	.795
	Quick Ratio (X)	.123	.707
4.	Current Ratio (X)	.124	.732
	Revenue from Operations/Share (Rs.)	.882	.738
	Quick Ratio (X)	.123	.671
	Asset Turnover Ratio (%)	.983	.665
5.	Current Ratio (X)	.118	.667
	Revenue from Operations/Share (Rs.)	.877	.692
	Quick Ratio (X)	.117	.627
	Asset Turnover Ratio (%)	.949	.646
	Cash Earnings Retention Ratio (%)	.912	.634
6.	Current Ratio (X)	.103	.662
	Revenue from Operations/Share (Rs.)	.873	.656
	Quick Ratio (X)	.102	.617
	Asset Turnover Ratio (%)	.888	.635
	Cash Earnings Retention Ratio (%)	.899	.615
	Market Cap/Net Operating Revenue (X)	.775	.607
7.	Current Ratio (X)	.103	.631
	Revenue from Operations/Share (Rs.)	.276	.638
	Quick Ratio (X)	.102	.589
	Asset Turnover Ratio (%)	.853	.620
	Cash Earnings Retention Ratio (%)	.897	.586
	Market Cap/Net Operating Revenue (X)	.568	.603
	PBDIT/Share (Rs.)	.226	.584
8.	Current Ratio (X)	.099	.625
	Revenue from Operations/Share (Rs.)	.276	.619
	Quick Ratio (X)	.088	.586
	Asset Turnover Ratio (%)	.683	.570
	Cash Earnings Retention Ratio (%)	.896	.571
	Market Cap/Net Operating Revenue (X)	.004	.565
	PBDIT/Share (Rs.)	.224	.572

Step	Variables	Tolerance	Wilks' lambda
	EV/Net Operating Revenue (X)	.005	.560

Wilks' lambda is a test statistic used in multivariate analysis of variance (MANOVA) to test whether there are differences between the means of identified groups of subjects on a combination of dependent variables. The Discriminant stepwise statistics (Table: 2) shows the Ratios in the form of variables used in analysis. The value of tolerance is close to 1 which shows that there is no problem of multi collinearity in the data. Wilks' Lambda depicts the values of two or more variables. Tolerance is the proportion of a variable's variance not accounted for by other independent variables in the equation. A variable with very low tolerance contributes less to a model and can cause computational problems.

Table 3: Wilks' Lambda

Step	Number of Variables	Lambda	Df1	Df2	Df3	Exact F		
						Statistic	df1	df2
1	1	.808	1	1	158	37.534	1	158.000
2	2	.707	2	1	158	32.504	2	157.000
3	3	.665	3	1	158	26.233	3	156.000
4	4	.634	4	1	158	22.397	4	155.000
5	5	.607	5	1	158	19.956	5	154.000
6	6	.584	6	1	158	18.170	6	153.000
7	7	.560	7	1	158	17.033	7	152.000
8	8	.546	8	1	158	15.691	8	151.000

Table 3 shows the results of univariate ANOVA's, carried out for each independent variable and are presented. Here the group statistics gives the distribution of observations into different groups. Since, in the present research we have categorized into two groups viz... 'Poor' as '1' and 'Good' Performer as '2', the SPSS has grouped the data into two groups. The total numbers of 158 shown in df3, observations group, which represent 100% of the observations, have been grouped for the Discriminant Analysis. The function indicates the first canonical linear discriminant function. Lambda shows the values of each variables in the model as calculated in Table 2, df1 values shows the number of variables, df2 values are the numbers allocated to variables, df3 shows the total number of observations in the model. F –statistic is used to determine whether the one-way MANOVA was statistically significant or not. The F-statistic values in Table shows that F-significance is there, as it will not consider insignificant values. Therefore, here we can conclude that there is the relationship between financial ratios and stock returns.

SUMMARY OF CANONICAL DISCRIMINANT FUNCTIONS

Table 4: Eigen values

Function	Eigen `value	% of Variance	Cumulative %	Canonical Correlation
1	.831[a]	100.0	100.0	.674

First 1 canonical discriminant functions were used in the analysis. The function indicates the first canonical linear discriminant function. The number of function depends on the discriminating variables. Since in the present research we have used two discrimination variables, one function has been calculated by SPSS. The function gives the projection of the data which is best discriminant between the groups.

Eigen Values

The Eigen values are related to the canonical correlations and describe how best discriminating ability the functions possess. The % of variances is the discriminating ability of the 2 groups. Since there is only one function, 100% of the variance is accounted by this function. The cumulative % of the variance gives the current and proceeding cumulative total of the variance. As mentioned above, as there is only one function in the present research we have 100% of the cumulative variance. The canonical correlations of our predictor variables viz. Poor stock market performer or Good stock market performer and the grouping of the job is given in the above Table 4. The Eigen value gives the proportion of variance explained. A larger Eigen value explains a strong function. The canonical relation is a correlation between the discriminant scores and the levels of these dependent variables. The higher the correlations value, the better the function that discriminates the values. 1 is considered as perfect. Here, we have the correlation of 0.674 is comparatively high.

Table 5: Standardized Canonical Discriminant Function Coefficients

	Function
	1
Revenue from Operations/Share (Rs.)	0.969
PBDIT/Share (Rs.)	-0.664
Asset Turnover Ratio (%)	0.365
Current Ratio (X)	1.676
Quick Ratio (X)	-1.306
Cash Earnings Retention Ratio (%)	0.33
EV/Net Operating Revenue (X)	-3.534
Market Cap/Net Operating Revenue (X)	4.069

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.546	93.176	8	.000

The Wilks' Lambda is one of the multivariate statistics. From the above Table 5 we will have to see the significance of Wilks' lambda significant value is 0.000, which shows it is significant. The lower the value of Wilks' Lambda, the better. In the present case the value is 0.546. The Chi-square is 93.176 with 8 degree of freedom, which is based on the groups present in the categorical variables. A Wilks' Lambda of 1.00 is when the observed group means are equal, while Wilks' Lambda is small when the within-groups variability is small compared to the total variability. This indicates that the group means appear to differ.

Checking For Relative Importance of Each Independent Variable

The standardized canonical discriminant coefficients can be used to rank the importance of each variable. A high standardized discriminant function coefficient might mean that the groups differ a lot on that variable. On comparing the standardised coefficient, it is possible to identify which independent variable is more discriminating than the other variables. The higher the discriminating powers the higher the standardised discriminant coefficient. The SPSS output of the Standardised Canonical discriminant function coefficient is given in the Table 6. The Market cap/Net Operating Revenue has the highest discriminating power due to the highest discriminant coefficient of 4.069 followed by current ratio, Revenue from operations/share, Asset turnover Ratio, Cash earnings Retention Ratio, PBDIT/share, Quick ratio & EV/Net operating Revenue. This indicates that the Market cap/Net Operating Revenue is the most important set of ratio, having impact on financial performance of the companies.

The standardized canonical discriminant function coefficient is used to calculate the discriminant score. The score is calculated as a predicted value from the linear regression using the above standardized coefficients and the standardised variables. Based on the coefficient above we can rank the relative important predictor variables as summarized below: -

Table 6: Ranking of the Variables

Ranking of the	Predictor Variable
1	Market cap/Net Operating Revenue
2	current ratio
3	Revenue from operations/share
4	Asset turnover Ratio
5	Cash earnings Retention Ratio
6	PBDIT/share
7	Quick ratio
8	EV/Net operating Revenue

Table 7: Unstandardized Canonical Discriminant Function Coefficients

	Function
	1
Revenue from Operations/Share (Rs.)	.004
PBDIT/Share (Rs.)	-0.008
Asset Turnover Ratio (%)	0.008
Current Ratio (X)	0.955
Quick Ratio (X)	-2.629
Cash Earnings Retention Ratio (%)	0.014
EV/Net Operating Revenue (X)	-0.750
Market Cap/Net Operating Revenue (X)	1.023
(Constant)	**-3.994**

Unstandardized coefficients

On the Basis of Unstanderdised Canonical Discriminant Coefficients, Formulating the Discriminant Function

The standard form of the Discriminant Function is

Z= a+v1x1+v2x2+…..vnxn

Where,

‘a’ is the constant term, which is in the table 8 viz. ‘Canonical Discriminant Function Coefficient’.

v1v2= are the corresponding unstandarised discriminant function coefficient

x1x2 = are the independent variables

Z=Discriminant Score

Where,

Z= -3.994+0.004(Revenue from Operations/Share) - 0.008(PBDIT/Share) +0.008 (Asset Turnover Ratio) + 0.955 (Current Ratio) – 2.629(Quick Ratio) + 0.014(Cash Earnings Retention Ratio) - 0.750 (EV/Net Operating Revenue) +1.023 (Market Cap/Net Operating Revenue).

Thus, the Canonical Discriminant Function Coefficient indicates the unstandardised scores of the independent variables.

Unstanderdised canonical discriminant coefficients followed the same pattern as it was followed in standerdised canonical discriminant coefficients, which shows that Market cap/Net Operating Revenue and current ratio are the important set of ratio, having impact on financial performance of the companies. Quick ratio and EV/Net operating Revenue are the set of ratios, having less impact on financial performance of companies.

Table: 8: Structure Matrix

	Function
	1
Current Ratio (X)	.535
Revenue from Operations/Share (Rs.)	.452
Quick Ratio (X)	.438
Cash Earnings Retention Ratio (%)	.339
Asset Turnover Ratio (%)	.286
PBDIT/Share (Rs.)	.258
Market Cap/Net Operating Revenue (X)	.069
EV/Net Operating Revenue (X)	.025

The canonical structure matrix reveals the correlation between each variable in the model and the discriminant functions. It allows us to compare correlations and see how closely a variable is related to each function. These values are calculated by pooled within –group's correlations between discriminating variables and standardized canonical discriminant functions variables ordered by absolute size of correlation with in function. Generally, any variables with a correlation of 0.3 or more are considered to be important. Here, we can see that there are four variables that are Current Ratio, Revenue from Operations/Share, Quick Ratio, Cash Earnings Retention Ratio, which plays important role to the discriminant function. The canonical structure matrix should be used to assign meaningful labels to the discriminant functions. The standardized discriminant function coefficients should be used to assess the importance of each independent variable's unique contribution to the discriminant function. Structure Matrix also shows that it does not follows same pattern as followed in the Canonical discriminant Function Coefficients.

Table 9: Functions at Group Centroids

Performance Group	Function
	1
1.0	-.789
2.0	1.041

The Canonical group means is also called group centroids, are the mean for each group's canonical observation. The larger the difference between the canonical group means, the better the predictive power of the canonical discriminant function in classifying observations.

Classification Statistics

Table 10: Prior Probabilities for Groups

Performance Group	Prior	Cases Used in Analysis	
		Unweighted	Weighted
1.0	0.500	91	91.000
2.0	0.500	69	69.000
Total	1.000	160	160.000

The prior probabilities give us the number of observations used in the analysis and the distribution of the observations into groups used as a starting point in the analysis. As above, Table 11 is showing that there are 160 observations used in analysis. It gives the weighted value, which is further used in the calculation of the centriod value. Since the 2 groups viz. the Poor and Good are not equal (91 Poor and 69 Good), we use weights on the centroids to find the dividing point.

The dividing rule will therefore be

$$= \frac{(n1)(\text{Lower Centriod}) + (n2)(\text{Higher Centriod})}{n1 + n2}$$

$$= \frac{(91 \times -0.789) + (69 \times 1.041)}{91+69}$$

= 0.0001875

Table 11: Classification Function Coefficients

	Performance Group	
	1.0	2.0
Revenue from Operations/Share (Rs.)	.006	.010
PBDIT/Share (Rs.)	-.018	-.033
Asset Turnover Ratio (%)	.107	.119
Current Ratio (X)	4.947	10.196
Quick Ratio (X)	1.615	-3.068
Cash Earnings Retention Ratio (%)	.157	.183
EV/Net Operating Revenue (X)	25.965	22.380
Market Cap/Net Operating Revenue (X)	-24.583	-20.406
(Constant)	-19.934	-28.135

The coefficients of linear discriminant function Table interprets the Fisher’s theory and is only available when linear model is selected for discriminant Function. The Linear discriminant functions, also called “classification functions’, for each observations. For one observation, we can compute it's score for each group by the coefficients. The observation should be assign to the group with highest score. In addition, the coefficients are helpful in deciding which variable affects more in classification. Comparing the values between groups, the higher coefficient means the variable attributes more for that group. As we can see (Table: 12) from group 1, EV/Net operating Revenue has the highest discriminating power due to the highest discriminant coefficient of 25.965 followed by current ratio, Quick ratio, Cash earnings Retention Ratio, Asset turnover Ratio, Revenue from operations/share, PBDIT/share & The Market cap/Net Operating Revenue and From Group 2, EV/Net operating Revenue has the highest discriminating power due to the highest discriminant coefficient of 22.380 followed by current ratio, Cash earnings Retention Ratio, Asset turnover Ratio,, Revenue from operations/share, PBDIT/share, Quick ratio & The Market cap/Net Operating Revenue. This shows that all these variables are important but EV/Net operating Revenue is the variable which affects more in classification.

Table 12: Descriptive Statistics

	N	Minimum	Maximum	Sum	Mean	Std. Deviation
Discriminant Scores from Function 1 for Analysis 1	91	-2.67884	1.49797	-71.79585	-.7889654	.84485783
Valid N (listwise)	91					

Performance Group = 1.

Table 13: Descriptive Statistics

	N	Minimum	Maximum	Sum	Mean	Std. Deviation
Discriminant Scores from Function 1 for Analysis 1	69	-1.40061	4.41619	71.79585	1.0405196	1.17422924
Valid N (listwise)	69					

Mean values are the Discriminant Scores

Table 14: Classification Results

		Performance Group	Predicted Group Membership		Total
			1.0	2.0	
Original	Count	1.0	79	12	91
		2.0	13	56	69
	%	1.0	86.8	13.2	100.0
		2.0	18.8	81.2	100.0

84.4% of original grouped cases correctly classified

It has been observed that 84.4% of data was correctly classified as Poor Performer and Good Performer in the Industry by the discriminant function. It has also been noticed that out of 91 observations, 79 observations have been correctly classified the companies under performance group 1, that is “Poor”. Whereas 12 observations have been wrongly classified the companies under performance group 2, that is “Good”. Out of the 69 observations, 56 observations have been correctly classified the companies under performance group 2, that is “Good” and 19 observations have been wrongly classified as the companies under performance group 1, that is “Poor”. The accuracy of the model may hence be considered adequate. This indicates a very good predictive capacity of the discriminant function. It has the capacity to predict whether a company would have the potential to be a potential “Good” performer and “Poor” performer.

CONCLUSIONS

The study is to analyse and compare the performances of the automobile companies listed on National Stock

Exchange in India and to find the discriminatory power of the sets of Ratios which are having impact on financial performance of the companies. To identify the important set of ratios which are having impact on financial performance of the companies Wilks' Lambda with Multiple discriminate analysis model is used. Average market stock returns are used to classify the companies into "Good" stock market performer and "Poor" stock market performer (Table 1). A sample of fourteen automobile companies listed on national stock exchange will be selected. Market capitalization would be the basis for this selection. Study covers the period of Twelve years ranging from April 1, 2004 to March 31, 2016. Annual Stock Prices for the selected companies for this specific period would be used. The main focus of the paper is to investigate the relationship between financial ratios and stock returns. The Discriminant stepwise statistics (Table: 2) shows the Ratios in the form of variables used in analysis. F –statistic is used to determine whether the one-way MANOVA is statistically significant or not. The F-statistic (Table: 3) values shows that F-significance. Therefore it can conclude that there is the relationship between financial ratios and stock returns also Financial Variables (Ratios) has effect the Capital Structure. The model was tested successfully, as it has a good enough Eigen value (table: 4) and Wilks' lambda is also Significant (Table: 5). A basic model was developed to identify the potential Good performer and the Poor performer, based on the eight ratios identified by the Factor Analysis.

The model has classified 84.4 % of the groups correctly. This gives extremely high result of the model to come out with correct classifications of the Poor performer and the Good performer. The model has used eight ratios as predictor variables and standardized canonical discriminant coefficients are used rank the importance of each variable. The Market cap/Net Operating Revenue has the highest discriminating power due to the highest discriminant coefficient (Table: 5) of 4.069 followed by current ratio, Revenue from operations/share, Asset turnover Ratio, Cash earnings Retention Ratio, PBDIT/share, Quick ratio & EV/Net operating Revenue. This indicates that the Market cap/Net Operating Revenue is the most important set of ratio, having impact on financial performance of the companies. The standardized canonical discriminant function coefficient is used to calculate the discriminant score (Z-score) for both the performance groups viz. -0.78896 for group 1, 1.0405 for Group 2 and also Z cut off rate is calculated from the centriod value viz. 0.0001875.

So, **the decision rule classification will be as under: -** Predict and classify as Poor Performer if

-0.789 < 0.0001875

Predict and classify as Good Performer if

a0.0001875 < 1.041

This shows that original Groups are correctly classified. This indicates a very good predictive capacity of the discriminant function. It has the capacity to predict whether a company would have the potential to be a "Good" stock market performer and "Poor" stock market performer. It has been found that financial variables viz. financial ratios have impact on the Capital Structure of the Automobile companies In India. The Market cap/Net Operating Revenue, Current ratio are the important set of ratio, having impact on financial performance of the companies. Revenue from operations/share, Asset turnover Ratio, Cash earnings Retention Ratio, PBDIT/share having moderate impact on financial performance of companies and Quick ratio and EV/Net operating Revenue are the set of ratios, having less impact on financial performance of companies. The discriminant analysis has revealed that the Atul Autos, Eicher Motors, Force Motors, Hero Motocorp, Maruti and VST tillers tractors limited are 'Good performers' and other companies that is Ashok Leyland, Bajaj Autos, Hind Motors, Honda Motocorp, Mahindra and Mahindra, Sundram clayton, Tata Motors and TVS automobiles are 'Poor Performers'.

REFERENCES

1. Bray, J. H., & Maxwell, S. E. (1982). Analyzing and interpreting significant MANOVA'S. Review of Educational Research, 52, 340- 367.
2. Brown, M. T., & Tinsley, H. E. A. (1983). Discriminant analysis. Journal of Leisure Research, 15, 290-310.
3. Campello, Murillo, 2003, Capital structure and product markets interactions: evidence from business cycles, Journal of Financial Economics 68, 353-378.
4. Danos, Paul, and John W. Eichenseher, 1982, Audit industry dynamics: Factors affecting changes in client industry market shares, Journal of Accounting Research 20, 604-616.
5. Dillon, W. R., & Goldstein, M. (1984). Multivariate analysis. New York: Wiley. Dixon
6. Divatia.P.J, Indian Industries in the 21st Century, 2003, Deep & Deep Publications Pvt Ltd, New Delhi.
7. Fama, Eugene F., and Kenneth R. French, 2005, Financing decisions: who issues stock? Journal of Financial Economics 76, 549-582.
8. Fisher, R. A. (1936). The use of multiple measurements in taxonomic problems. Annuals of Eugenics, L 179-188.
9. Gowri M., Sekar M. (2014), Assessing the Financial Health of Select Automobile Companies in India: A Quantitative approach Using the Z-Score Multi-discriminant Financial Analysis Model, Great Lakes Herald Vol. 8, No. 1, March 2014.
10. Gupta. S.P, 2000, Statistical Methods, Sultan Chand & Sons, New Delhi.
11. Gupta. S.P, Statistical Methods, Sultan Chand & Sons, New Delhi, 2000.
12. Huberty, C. J. (1975 b). The stability of three indices of variable contribution in discriminant analysis. Journal of Experimental Education, 44, 59-64. Klecka
13. Khan.M.Y & Jain.P.K, Financial Management, Tata McGraw Hill, New Delhi, 1996.
14. Korajczyk, Robert A., and Amnon Levy, 2003, Capital structure choice: Macroeconomic conditions and financial constraints, Journal of Financial Economics 68, 75-109.
15. Kothari.C.R, Research Methodology, Methods & Techniques, New Age International (P) Limited Publishers, New Delhi, 1990.
16. M. Pandey, Financial Management, Vikas publishing house Private limited, New Delhi.
17. Making vocational choices: A theory of careers. Englewood Cliffs, N J: Prentice-Hall. Holland, J. L. (1978).
18. Michael R. Roberts, Amir Sufi (2009), Control Rights and Capital Structure: An Empirical Investigation, the Journal of Finance, VOL. LXIV, NO. 4.

19. Murray Z. Frank and Vidhan K. Goyal (2009), Capital Structure Decisions: Which Factors are reliably important? Financial Management, spring 2009, volume8, pages 1 – 37.
20. Myers, Stewart C. (1984), Capital Structure Puzzle, Journal of Finance, Vol. 39, No. 3, pp. 575-592.
21. Nikolaos Eriotis, Dimitrios Vasiliou, Zoe Ventoura-Neokosmidi, (2007), How firm characteristics affect capital structure: an empirical study, Managerial Finance, Vol. 33 Issue: 5, pp.321 – 331.
22. Pathak Joy, (2010), What Determines Capital Structure of Listed Firms in India? SSRN, 1561145
23. Rajan, R. and Zingales, L. 1995. "What do we know about capital structure? Some evidence from international data", Journal of Finance, Vol. 50, pp. 1421- 1460
24. Rajendra.R.Vaidya, The Structure of Indian Industry, Oxford University Press, New Delhi, 2004.
25. S. K. Gupta and R. K. Sharma, Management Accounting, Kalyani Publishers, Bangalore.
26. S. Ross (1977), The Determination of Financial Structure: The Incentive-Signaling Approach, Bell Journal of Economics, Vol. 8 (Spring), 23
27. Saravanan S. Dr. and Abarna J., "A Study on Liquidity analysis of selected Automobile Companies in India", Indian Journal of Applied Research, February 2014,Vol. 4,Issue 2, PP 6-8.
28. Soku Byoun (2008), How and When Do Firms Adjust Their Capital Structures toward Targets?, The Journal Of Finance, VOL. LXIII, NO. 6.
29. Tim C. Opler, Sheridan Titman (1994), Financial Distress and Corporate Performance, The Journal of Finance, Vol. 49, No. 3, pp. 1015-1040.
30. Valeriy Sibilkov (2009), Asset Liquidity and Capital Structure, Journal of Financial and Quantitative Analysis Vol. 44, No. 5, pp. 1173–1196.
31. Vidya R., Krishnaveni M.(2016), a study on liquidity assessment of scooters and three wheelers sector in Indian automobile industry, Asia pacific journal of finance, Vol: I. Issue XLII.
32. Wald (1999), ―How firm characteristics affect capital structure: An international Comparison‖, Journal of Financial Research 22, 161–187.