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Financial Ratios Performance of Major Indian Industries to Evaluate their Performances using Multivariate Analyses and Perceptual Mapping

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The present research is aimed at analyzing financial performances of companies to assess their financial strengths and enable the decision makers to understand the financial scenario of their firms. The dataset relates to 247 companies from five major industries in the Indian corporate database. The time frame of the data pertaining to the present study is 2001-2010. The salient feature of this study is the application of *Factor*, *K-means clustering, Discriminant Analyses* and *Perceptual Mapping* as data mining tools to explore the hidden structures present in the dataset for each of the study periods (Anderson, 1984). Factor analysis is applied first and the factor scores of extracted factors are used to find initial groups by K-means clustering algorithm. A few outlier industries, which could not be classified to any of the groups, are discarded as some of the ratios possessed unusual values. Finally, attribute based perceptual mapping is applied and the groups are identified as companies belonging to **H**-Class (High performance), **M**-Class **(**Moderate performance**)** and **L**-Class (Low performance). The results of the present study indicate that *Perceptual maps* can be used as a feasible tool for the analysis of large set of financial data.

Keywords: *Financial Ratios, Data mining, Factor Analysis, K-means Clustering, Discriminant Analysis, Perceptual Map (PM)*

1.0 INTRODUCTION

Financial parameters of banks and industries have been used in forecasting failure and bankruptcy over the past four decades. Beaver's study changed the way such analyses are conducted in the field of evaluating and forecasting potential company failures and bankruptcies (Beaver, 1966). One approach is to explore for the best predictors that lead to minimum misclassification errors while the other is to select the statistical method that would lead to improved correct classification with greater accuracy. The company failure does have unpleasant consequences for its shareholders as well as its employees. Hence there seem to be continued interests in bankruptcy and failure models. It is generally recognized that company financial statements provide information on a company's performance, stability and indication of future commercial and financial prospectus. Analysis and interpretation of financial statements using various financial ratios may provide a shareholder, creditor or banker, useful information about the company's financial status, position, and also borrowing power.

2.0 BRIEF REVIEW OF LITERATURE

Financial ratio analysis involves comparing the relationship between figures in the financial statements in relative terms. Financial ratios appear frequently in company annual reports, auditors' reports and internal management reports. Green (1978) stated that financial ratios have long been regarded as barometers of corporate health, being used for reporting liquidity, leverage, productivity and profitability, and that an investor may use financial ratios to appraise a company's performance and its future prospect of success. Chen and Shimerda (1981) have shown that financial ratios played an important role in evaluating the financial conditions of an entity. Further, based on their analytical studies over the years, they have demonstrated the usefulness of financial ratios. Chandrasekaran and Manimannan, *et al.* (2011) have graded companies that reflected the performance of companies based on certain financial ratios.

The earliest study using multivariate data analysis on failure prediction was conducted by Altman (1968) using a set of financial and economic ratios as possible determinants of corporate failures. The study used sixty six companies from manufacturing industries comprising of bankrupt and non-bankrupt firms and twenty two ratios from five categories, namely, liquidity, profitability, leverage, solvency and activity. Five ratios were finally selected for their performance in the prediction of corporate bankruptcy and the derived model correctly classified 95 percent of the total sample one year prior to bankruptcy. The percentage of accuracy declined with increasing number of years before bankruptcy. Altman (1994) reported the use of neural network in identification of distressed business by the Italian central bank. Using 1000 sampled firms with ten financial ratios as independent variables, the found that the neural network is not a clearly dominant mathematical model technique compared to traditional statistical techniques. Other studies relating to company failure and bankruptcy using financial parameters are reported in Beaver (1966), Chen and Shimerda (1981), Gepp and Kumar (2008), Green (1978) and Li and Sun (2010).

The objective of the present study is to uncover the intrinsic groups or classes and identify the most influencing ratios that would reflect the performance of top ranking companies in India, using the concepts of data mining, factor analysis, multivariate discriminant analysis and perceptual map.

3.0 METHODOLOGY

This section brings out the discussion of the database, the ratios selected and the Data Mining Techniques.

3.1. DATABASE AND SELECTION OF VARIABLES

The financial data published by *Capital Market* (Indian Corporate Database) was considered as the database. The data mainly consists of five major types of industries in India and under each type of industry, there are several companies. The data consists of financial ratios of each company for the time period of ten years (from 2001 to 2010), around 120 copanies. Among the listed companies, number of companies varied over the study period owing to removal of those companies for which the required data are not available. In this study, 14 ratios are carefully chosen among the many that had been used in previous studies *(Table 1)*. These 14 ratios are chosen to assess profitability, solvency, liquidity, and cash-equity ratio. The choice of ratios used is based on two main criteria, namely their popularity as evidenced by their frequent usage in the finance and accounting literature and that the ratios have been shown to perform well in previous studies.

3.2 DATA MINING TECHNIQUES

Although data mining is relatively a new term, the technology is not. Data Mining or Knowledge Discovery in Databases (KDD) is the process of discovering previously hitherto unknown and potentially useful information from the data in databases. In the present context, data mining exhibits the patterns by applying few techniques namely, factor analysis, **k**-means clustering and discriminant rule.

As such KDD is an iterative process, which mainly consists of the following steps:

Step 1: Data cleaning; ***Step 2*:** Data Integration; ***Step 3***: Data selection and transformation;

*S**tep 4***: Data Mining and *S**tep 5***: Knowledge representation.

Of the above iterative process, Steps 4 and 5 are very important. If appropriate techniques are applied in Step 5, it provides potentially useful information that explains the hidden structure. This structure discovers knowledge that is represented visually to the user, which is the final phase of data mining.

3.2.1 FACTOR ANALYSIS

Factor analysis provides the tools for analyzing the structure of the interrelationships (correlations) among the large number of variables by defining sets of variables, mostly labeled, that are highly interrelated, known as factors (Anderson, 1984). In the present study, factor analysis is initiated to uncover the patterns underlying financial ratio variables (*Table 1*). In factor extraction method the number of factors is decided based on the proportion of sample variance explained. Orthogonal rotations such as Varimax and Quartimax rotations are used to measure the similarity of a variable with a factor by its factor loading (Everitt and Dunn, 2001; Hair, Black, Babin and Anderson, 2010).

TABLE 1. LIST OF FINANCIAL PARAMETERS USED IN THE PRESENT STUDY

Ratios	Description	Ratios	Description
DEB_EQU	Debt - Equity Ratio	PBDITM	Profit Before Depreciation Interest Tax Margin
LONG_TE	Long Term Debt-Equity Ratio	PBITM	Profit Before Interest Tax Margin
CURREN	Current Ratio	PBDTM	Profit Before Depreciation Tax Margin
FIX_ASS	Fixed Assts	CPM	Current Profit Margin
INVENTO	Inventory	APATM	Adjusted Profit After Tax Margin
DEBTORS	Debtors	ROCE	Return on Capital Employed
INTERES	Interest	RONW	Return on Net Worth

3.2.2. K-MEANS CLUSTERING METHODS

Nonhierarchical clustering techniques are designed to group *items,* rather than *variables,* into a collection of K clusters (Everitt and Dunn, 2001; Hair, Black, Babin and Anderson, 2010). The number of clusters, K, may either be specified in advance or determined as part of the clustering procedure. The term K-means method is coined for describing an algorithm that assigns items to the k-clusters having the nearest centroid (mean). Generally this technique uses Euclidean distances measures computed by variables. Since the group labels are unknown for the data set, **k**-means clustering is one such technique in applied statistics that discovers acceptable classes, in the present study, groups of companies.

3.3.3 DISCRIMINANT ANALYSIS

Multivariate Discriminant Analysis is a multivariate technique using several variables simultaneously to classify an observation vector into one of several a priori groups of companies as obtained by the K-means method. In the present study, discriminant analysis is used to exhibit groups graphically and judge the nature of overall performance of the companies (Everitt and Dunn, 2001; Hair, Black, Babin and Anderson, 2010).

3.3.4 PERCEPTUAL MAP

Perceptual mapping has been used as a strategic management tool for about thirty years. It offers a unique ability to communicate the complex relationships between marketplace competitors and the criteria used by buyers in making purchase decisions and recommendations. Its powerful graphic simplicity appeals to senior management and can stimulate discussion and strategic thinking at all levels of all several types of organizations. Perceptual mapping can be used to plot the interrelationships of consumer products, industrial goods, institutions, as well as populations.

Virtually any subjects that can be rated on a range of attributes can be mapped to show their relative positions in relation both to other subjects as well as to the evaluative attributes. Perceptual maps may be used for company performance, concept development and evaluation, and tracking changes in companies perceptions among other uses. In this paper, perceptual map is used to identify contribution of financial ratios to different groups of companies.

4.0 ALGORITHMS

A brief step-by-step algorithm to grade the companies during each of the study period based on their overall performances is described below:

Step 1: Factor analysis is initiated to find the structural pattern underlying the data set.

Step 2: **K** –means analysis is used to partition the data set into **k**-clusters using the factor scores obtained in **Step 1** as input.

Step 3: Discriminant analysis is then performed with the original ratios by considering the groups formed by the **k**-means algorithm.

Step 4: Perceptual map is drawn with the standardized canonical discriminant function and centroid values of financial parameters of groups of companies.

5.0 RESULTS AND DISCUSSION

As mentioned in *Section 3.2.1,* Varimax and Quartimax criterion for orthogonal rotation have been used for the pruned data. Even though the results obtained by both the criterions were very similar, the varimax rotation provided relatively better clustering of financial ratios.

Consequently, only the results of varimax rotation are reported here. We have decided to retain 75 percent of total variation in the data, and thus accounted consistently *four factors* for each year with eigen values little less than or equal to unity. *Table 2* shows variance accounted for each factors.

TABLE 2. PERCENTAGE OF VARIANCE EXPLAINED BY FACTORS

Factors	Variance explained				
	2001	**2002**	**2003**	**2004**	**2005**
1	37.06	37.85	35.58	35.85	40.22
2	17.00	15.33	18.78	16.84	19.21
3	14.39	14.63	13.53	14.07	11.30
4	8.43	8.50	8.30	8.28	7.88
Total	**76.88**	**76.31**	**76.19**	**75.04**	**78.61**
	2006	**2007**	**2008**	**2009**	**2010**
1	33.24	38.42	39.06	38.14	37.43
2	16.63	13.82	15.59	18.26	16.88
3	14.47	12.49	11.29	10.17	11.61
4	13.30	11.17	9.68	9.21	9.46
Total	**77.64**	**75.90**	**75.62**	**75.78**	**75.38**

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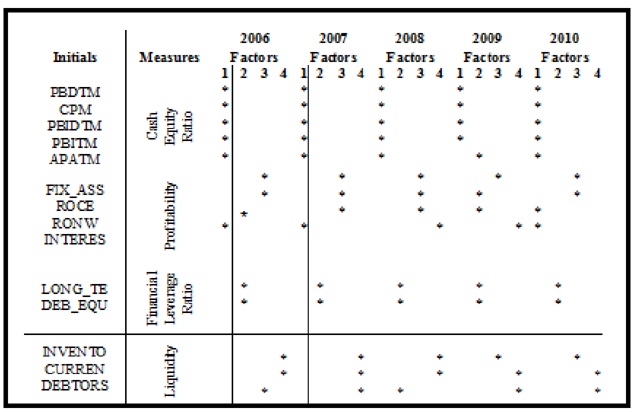
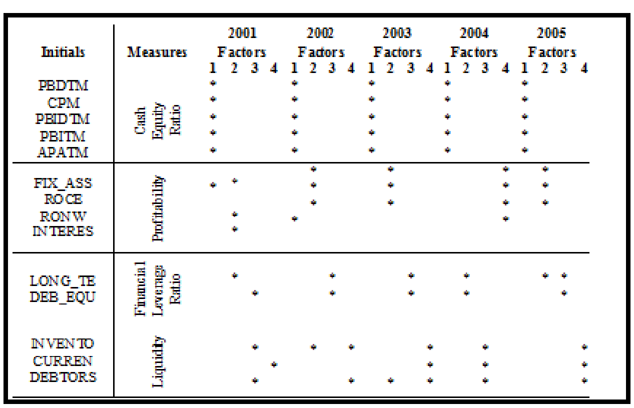
From the above table we observe that the total variances explained by the extracted factors are over 75 percent, which are relatively high. Also, for each factors the variability is more or less the same for the study period, though the number of companies in each year, after data cleaning and selection, kept varying owing to various reasons.

The financial ratios loaded in the factors are presented in *Table 3*. Only those ratios with higher loadings are indicated by (*) symbol. From the *Table 3* it is clear that the clustering of financial ratios is stable during the study period. We observe slight changes in factor loadings during the periods considered. The differences in factor loadings may be due to statistical variations in the original data.

TABLE 3. FINANCIAL RATIOS IN ROTATED FACTORS (YEAR -WISE)





**** Indicates financial ratios highly loaded in respective factors***

After performing factor analysis, the next step is to assign initial group labels to each company. Step 2 of the algorithm is applied with factor scores extracted by Step 1, by conventional **k**-means clustering analysis. Formations of clusters are explored by considering 2-clusters, 3-clusters, 4-cluster and so on. Out of all the possible trials, 3-cluster exhibited meaningful interpretation than two, four and higher clusters. Having decided to consider only 3 clusters, it is possible to rate a company as Grade **H**, Grade **M** or Grade **L** depending on whether the company belonged to Cluster 1, Cluster 2 or Cluster 3 respectively.

Cluster 1 (Grade **H**) is a group of companies that have high values for the financial ratios, indicating that these companies are performing well. The companies with lower values for the financial ratios are grouped into Cluster 3 (Grade **L**). This suggested that Cluster 3 is a group of companies with low-profile. Cluster 2 (Grade **M**) are those companies which perform moderately well as compared to the Cluster 1 and Cluster 3. In spite of incorporating the results for each year, only the summary statistics are reported in *Table4.*

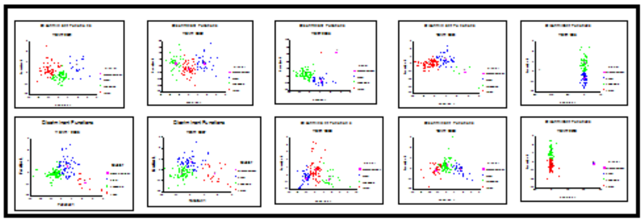
TABLE 4. NUMBER OF COMPANIES IN THE CLUSTERS

Years	Initial Cluster			Discriminant Classification		
	1	**2**	**3**	**1**	**2**	**3**
2001	17	55	47	47	55	17
2002	32	52	35	52	35	32
2003	30	86	03	04	86	29
2004	06	32	81	81	06	32
2005	55	63	01	01	55	63
2006	10	44	65	10	65	44
2007	17	41	61	17	61	41
2008	23	58	38	58	23	38
2009	27	57	35	35	57	27
2010	44	74	01	74	44	01

1 – Grade **H** 2 – Grade **M** 3 – Grade **L**

Table 4 indicates that majority of companies are in the moderate performance category except for the year 2004 and 2006. The possible reasons that kept most of the companies in lower profile in the year 2004 and 2006 may be due to the then government policies. And also MNC's have found their way to open business in India, pushing Indian companies back. *Figures 1* through *10* shows the groupings of companies into 3 clusters for each year of the study period. It is interesting to note that the mean vectors of these clusters can be arranged in the increasing order of magnitude as show in *Table 4*.

FIGURES 1 – 10. CLUSTERED GROUPS

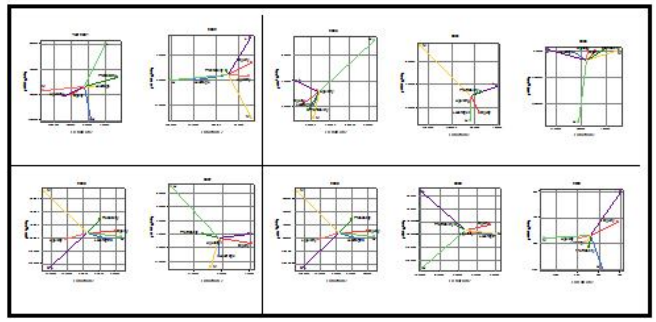


In order to identify the factors that are mainly responsible for the formation of the groups, perceptual mapping is drawn using the standardized discriminant coefficients and the unstandardised discriminant functions evaluated at the group centroids. From the perceptual maps in *Figure 11*, it is evident that the three groups of rated companies are very well separated and represented in the perceptual maps for all the ten year periods.

The two-dimensional graph clearly indicates that, in the year 2001, dimension 1 comprises ***Liquidity and Equity ratios factor***, the dimension 2, ***Profitability and Leverage ratios factor***. In the year 2002, dimension 1 seems to comprise ***Equity and Profitability ratios factor*** and dimension 2, ***Liquidity, Leverage ratios factor.*** In the year 2003, in dimension 1, ***Liquidity ratio factor*** and dimension 1 accommodates only ***Equity, Leverage and Profitability ratio factor.*** In the year 2004, in dimension 1 seems to comprise ***Profitability ratio factor,*** and in dimension 2, ***Leverage, Equity and Liquidity ratios factor***. In the year 2005, in dimension 2, ***Equity, and Profitability ratios factor*****,** in dimension 1 comprises of ***Leverage and Liquidity ratios factor.***

In the year 2006, dimension 1 consists of ***Profitability and Liquidity ratios factor***, and the dimension 2, ***Equity and Leverage ratios factor***. In the year 2007, ***Profitability and Liquidity ratios*** in dimension 1, and ***Equity and Leverage ratios factor*** in dimension 2. In the year 2008, dimension 1 consists of ***Liquidity, equity and Leverage ratios factor***, and in dimension 2 ***Profitability ratio factor.*** In the year 2009, dimension 2 consists of ***Profitability, Liquidity and leverage ratios factor,*** and dimension 1 comprises ***Equity ratio***. In the year 2010, ***Liquidity, Leverage ratios*** in dimension 2 and ***Equity ratio factor*** in dimension 1. It is interesting to note that in all the ten years, all financial ratios contribute the company position to some extent.

Figure 11. Perceptual Maps for the years 2001 – 2010.



6.0 CONCLUSION

The purpose of this paper is to identify the meaningful groups of companies that are rated as best with respect to their performance in terms of financial ratios using data mining and perceptual map techniques. An attempt is made to analysis the financial data relating to major industries of public and private sector companies over a period of ten years from 2001 to 2010. The present analysis has shown that only 3 groups could be meaningfully formed for each year. This indicates that only 3 types of companies existed over a period of ten years. Further, the companies find themselves classified into *High* (Grade **H**)*, Medium* (Grade **M**) and *Low* (Grade **L**) categories depending on the financial ratios. Financial Analyst can make use of these techniques of rating, and the companies can project the performance on the basis of financial ratios that has been considered in this study. Perceptual maps may be used for financial ratios performance and evaluation, and tracking changes in companies perceptions, among other uses. A generalization of the results is under investigation to obtain a set of 3 groups of companies for any given year.

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