Forecasting Stock Performance in Indian Market using Multinomial Logistic Regression

Gautam Bandyopadhyay
National Institute of Technology, Durgapur

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Arun Upadhyay
Department of Management Studies
NSHM College of Management and Technology, Durgapur, India

Gautam Bandyopadhyay
Department of Management Studies
National Institute of Technology, Durgapur, India

Avijan Dutta
Department of Management Studies
National Institute of Technology, Durgapur, India

Abstract
The objective of this paper is to predict the outperforming stock with the help of Multinomial Logistic Regression (MLR). This paper uses financial ratios as usable selection criteria for determining performance in the stock market i.e. into three categories GOOD, AVERAGE and POOR based on the stock return and variance comparing with market return and variance. The sample of the study consists of 30 large market capitalization companies' ratio of four years, which are actively traded in the Indian Stock Market. Using various financial ratios as the independent variables, this study investigates and determines the financial indicators that significantly affect the share performance by using Multi Logistic Regression Method.
A Multi Logistic Regression was constructed with seven financial ratios i.e., Book Value (BV), PBIDT/Sales(PBIDTS) and Earnings per Share(EPS), Percentage change in operating profit(OP), Percentage change in net sales(NS),Price to Cash earnings per share(PECEPS), Price to book value(PEBV). The classification results showed high predictive accuracy rates of 56.8%.The model developed here can enhance an investor's stock price forecasting ability. The macro-ecomonic variable which also can influence the share price has not taken into account. The paper dicusses the practical implications , how Multinomial Logistic regression method can be used for prediction of the probability of good stock performance .The model can be used by investors, fund manager and investment companies to enhance their abilty to pick outperforming stock. This paper adds value to equity investor, fund manager, investment companies . So far in India no attempt has been made to use Multi logistic regression to predict stock performance with the help of financial ratios.This paper examines , how it can be used for prediction of stock market return in the Indian market.

Keywords: Stock Performance, Indian Stock Market, Multinomial Logistic Regression, Rate of Return.

Introduction

Global crashes do not occur all of a sudden but are headed by local and regional crashes in emerging economies. Even when the investors are not exposed to emerging stock markets, they should pay attention to these markets, as local crashes can affect developed markets. Moreover, the interdependence is relevant as well, in that interest rates, bond returns and volatility also affect the probabilities of the different types of stock market crashes.

It is important for shareholders and potential investors to use relevant financial information to enable them to make good investment decisions in the stock market. Prediction of stock performance is certainly very complicated and difficult task. In the history of stock performance literature, no comprehensive accurate model has been suggested till date for prediction of the stock market performance. The stock performance to some extent can be analyzed based on financial indicators reported in company's annual report. The annual report gives vast amount of information therefore these financial data are to be transformed into various ratios. Previous literature suggests that financial ratios have been recognized as important tools for assessing future stock performance. Analysts, investors and researchers use financial ratio for projection of future stock price trends. The ratio analysis has emerged as one of the key parameters for fund managers and the investors to determine the intrinsic value of the shares and thus financial ratios are extensively used for valuation of stock. This has already emerged as new discipline after the stock market crash in the 1990's and early 2000's in United States, parts of Europe and South Asia. Now-a-days the ratios are extensively used in fundamental analysis in prediction of the future performance of the company. The various new ratios like book value, price/cash earnings per share have been included to this discipline for valuation of share.

Financial ratios help to form the basis of investor stock price expectations and, hence, influence investment decision making. The level of importance given to the financial ratios differs from industry to industry and from one country to another country. So selecting appropriate ratios is very crucial to increase the prediction success rate. The objective of this paper is to apply statistical methods to survey and analyze financial data to develop a simplified model for interpretation. This study aims at developing a model for classifying into three categories based on their rate of return i.e. good, average or poor. In this study Multinomial Logistic Regression (MLR) method has been applied for classifying the selected companies based on their performance. Multi Logistic regression method is used here for prediction of the probability of good stock performance by fitting the variables to a logistic curve.

Literature Review

Logistic Regression, which is helpful for prediction of the presence or absence of a characteristic or outcome based on values of a set of predictor variables, is a multivariate analysis model (Lee, 2004). The applications of Logistic Regression have repeatedly been used in the area of corporate finance, banking and investments. Multivariate Discriminant Analysis has been used by many researchers for the default-prediction model; Altman, being the pioneer in this work in the year 1968 while Logistic Regression was used by the Ohlson to construct the default-prediction model in 1980. The early research on default prediction focuses on classifying firms as either defaulters or non-defaulters. Ohlson identifies that this assumption of default prediction is an equal payoff state. Clearly, misclassifying a defaulted firm as a non-defaulted firm will have repercussions that are more severe for an investor or a loan officer than the opposite case. As such, this research focuses on the ability of the models to accurately rank defaulted and non-defaulted firms based on their default probability. In predicting financial distress and bankruptcy which have been widely applied as the evaluation models providing credit-risk information, Logistic Regression was used by Ohlson (1980) which was then followed by several authors such as Zavgren (1985). Subsequently the same trend opted by Zmijewski (1984) for a Probit Analysis.

At the time of prediction with the help of Multivariate Discriminant Analysis, it assumes that the groups are of similar size as while predicting the default and non-default firms in the prediction carried out by Altman (1968) and subsequent researchers, it was shown that the number of non-default firms was never more than twice the number of default firms. However, default or bankruptcy being a rare event, a very high proportion of the non-defaulters was excluded from the analysis. Besides using ratios for prediction of corporate fiascos, these were also used for scaling or grouping industries according to the degree of risk. Horrigan (1965) found financial ratios as successful predictors for bond rating. Metnyk and Mathur (1972) used ratios to classify corporations into similar risk groups and attempted to relate them to the companies' market rates of return. But they could not report favorable results. O" Connar (1973) Studied five ratios namely a) total liabilities to net worth b) working capital to sales c) cash flow to number of common share d) earnings per share to price per share and e) current liabilities to inventory, but found them to be poor indicators of return on common stock. The different methodologies and financial ratios are used by various authors in order to classify firms' performance. Kumar and Ravi (2007) carried out a comprehensive review on various work related to the bankruptcy prediction problems. He indicated that neural network is most widely used technique followed by statistical models. McConnell, Haslem and Gibson (1986)) have identified that qualitative data can provide additional information to forecast stock price performance more accurately

Logistic Regression technique yields coefficients for each independent variable based on a sample of data (Huang, Chai and Peng, 2007). Logistic regression models (LRM) with two or more explanatory variables are widely used in practice (Haines and Others, 2007). The parameters of the logistic regression model are commonly estimated by maximum Likelihood (Pardo, Pardo and Pardo, 2005). The advantage of logistic regression is that, through the addition of an appropriate link function to the usual linear regression model, the variables may be either continuous or discrete, or any combination of both types, and they do not necessarily have normal distributions (Lee, 2004).

The predictor values from the analysis can be interpreted as probabilities (0 or 1 outcome) or membership in the target groups (categorical dependent variables). It has been observed that the probability of a 0 or 1 outcome is a non-liner function of the logit (Nepal, 2003). Logistic Regression is useful for situations in which it is required to predict the presence or absence of a characteristic or outcome based on values of a set of predictor variables. It is similar to a linear regression model but is proficient to models where the dependent variable is dichotomous. Logistic Regression coefficients can be used to estimate odd ratios for each of the independent variables in the model. Logistic Regression helps to form a multivariate regression between a dependent variable and several independent variables (Lee, Ryu and Kim, 2007). It is designed to estimate the parameters of a multivariate explanatory model in situations where the dependent variable is dichotomous, and the independent variables are continuous or categorical.

Existing literature indicates MLR has not been used to build a model for predicting outperforming shares. LR has been mostly used for prediction of financial distress and business failure. MLR has not been used for predicting share performance in India. In terms of investment destination in share, India is one top performing emerging market. In this context the present study will provide useful information to shareholders and potential investors to enable them to make good decisions regarding investments.

Research Objective and Methodology

In this study, the relation between financial ratios and stock performance of the firms has been analyzed with the help of Multi logistic regression. The earlier studies mentioned above have generally indicated that Logistic Regression, as used in the finance discipline, can be used as an effective tool to the decision makers. It has also been recognized that financial ratios can enhance an investor's stock price forecasting ability

The objective of the study aims at building a model using financial ratios of the firms for prediction of outperforming shares in Indian Stock Market Thus this study answer two question 1) Whether the yields of stocks can be explained with the help financial ratios? 2) Can we analyze stocks yields with Multi logistic regression model? The study also examines the efficacy of ratios as predictors of stock performance.

3.1 Analysis of model-Multi Logistic Regression

According to Wikipedia multinomial logit model, also known as multinomial logistic regression is a regression model which generalizes logistic regression by allowing more than two discrete outcomes. That is, it is a model that is used to predict the probabilities of the different possible outcomes of a categorically distributed dependent variable, given a set of independent variables (which may be real-valued, binary-valued, categorical-valued, etc.). Multinomial logit regression is used when the dependent variable in question is nominal (a set of categories which cannot be ordered in any meaningful way, also known as *categorical*) and consists of more than two categories.

Logistic Model with three categories has two logit functions:

(i). Logit Function for Y = 0 relative to logit function for Y = 2
(ii). LogitFunction for Y = 1 relative to logit function for Y = 2

Category Y = 2 is called a *reference group*.
$\log\ p/1\text{-}p = A + B_1X_1 + \ldots\ldots\ldots\ldots + B_kX_k$
$\log(g(1)) = A_1 + B_{11}\ X_1 + \ldots\ldots\ldots\ldots\ldots\ldots + B_{1k}X_k$
$\log((g(2)) = A_2 + B_{12}X_1 + \ldots\ldots\ldots\ldots\ldots + B_{2k}X_k$
$\log(g(3)) = \log 1 = 0$

In Multi logistic regression we have the following:

$$f(1) = \frac{g(1)}{g(1)+g(2)+1} = \frac{e^{A_1+B_{11}X_1+...+B_{1k}X_k}}{e^{A_1+B_{11}X_1+...+B_{1k}X_k} + e^{A_2+B_{21}X_1+...+B_{2k}X_k} + 1}$$

$$f(2) = \frac{g(2)}{g(1)+g(2)+1} = \frac{e^{A_2+B_{21}X_1+...+B_{2k}X_k}}{e^{A_1+B_{11}X_1+...+B_{1k}X_k} + e^{A_2+B_{21}X_1+...+B_{2k}X_k} + 1}$$

$$f(3) = \frac{g(3)}{g(1)+g(2)+1} = \frac{1}{e^{A_1+B_{11}X_1+...+B_{1k}X_k} + e^{A_2+B_{21}X_1+...+B_{2k}X_k} + 1}$$

Here we assume f(1) to be probability of poor, f(2) to be probability of average and f(3) to be probability of good.

If we put the values of the independent variables in the equations above we get the values ranging from 0 to 1 subject to f(1) +f(2) +f(3)=1 .After putting the values if f(1) >= 0.5 then it is classified as Poor or if f(2) >= 0.5 then it is classified as Average or if f(3) >=0.5 then it is classified as GOOD and if all the values of f(1) ,f(2) and f(3) are <0.5 then it is unclassified.

Logistic Regression analysis does not require the restrictive assumptions regarding normality distribution of independent variables or equal dispersion matrices nor concerning the prior probabilities of failure (Ohlson, 1980; Zavgren, 1985). Rather, logistic regression is based on two assumptions; (1) it requires the dependent variable to be dichotomous, with the groups being discrete, non-overlapping and identifiable and (2) it considers the cost of type I and type II error rates in the selection of the optimal cut-off probability. βs are the regression coefficients that are estimated through an iterative maximum likelihood method. However, due to the subjectivity of the choice of these misclassification costs in practice, most researchers minimize the total error rate and, hence, implicitly assume equal costs of type I and type II errors (Ohlson, 1980; Zavgren, 1985). Since multi logistics are the extension of binary logistic regression so all the assumptions are same but the dependent variable should be polychotomous.

Application of Multi Logistic Regression

Data Sources

In this context, we have taken the companies with large market capitalizations and most of these companies are part of Nifty index. The financial data used in this analysis have been collected from the web page (www.moneypore.com). The sample of the study is drawn from the 30 companies that are most actively traded in the Indian stock exchange as given in the Annexure II. We have collected financial ratios and stock price for calculating return. In this research a sample period consisting of four years, i.e., 2005-2008, have been taken for classification purposes.

For the purpose of carrying out Multi Logistic Regression analysis, we first need a method of classifying the performance of companies as Good, Average and Poor as there is no such definitive method.

Here in our research we have used a method that is very simple and objective: Mean return of a company’s stock over a given year rose above market return i,e sensex and the variance is less than market variance is classified as “GOOD”, Mean return is more than the sensex mean return and variance is more than market variance classified as “AVERAGE” , If the mean return is less than mean market return then it is classified as “POOR”. To obtain the return at the end of each financial year, we have used the March ending price for each year. Our sample was based on selection of 30 companies, for the years from 2005-2008. The study consists of a sample size of 118 distinct company-year observations and we have taken dependent variable as performance of the companies as good, average or poor and seven independent variables shown in Table No-3.

Three dependent variables that were considered for final analysis is given in Table 1
Table 1: Dependent variable

Type of Company based on stock market return	
GOOD	Mean return of a company's stock over a given year rose above market return i,e sensex and the variance is less than market variance is classified as "GOOD"
AVERAGE	Mean return is more than the sensex mean return and variance is more than market variance classified as "AVERAGE"
POOR	If the mean return is less than mean market return then it is classified as "POOR"

Mean return of a company's stock over a given year rose above market return i,e sensex and the variance is less it is classified as "GOOD", Mean return is more than the sensex return with maximum variance is classified as "AVERAGE" Otherwise it could be "POOR".
Table:- 2
Dependent variable Encoding

Original value	Internal value
GOOD	2
AVERAGE	1
POOR	0

We have encoded the dependent variables GOOD as '2', AVERAGE as '1' and POOR as '0'. Out of the 118 variables 29 were GOOD, 52 AVERAGE and 37 were POOR.

Table:3- Independent variables

Name of the Variables	Description of the variables
NS	Percentage Increase in Net sales
EPS	Earnings per Share
BV	Book Value
PECEPS	Price/Cash Earnings Per Share
PBIDTS	Profit Before Interest Depreciation and Tax/Sales
PEBV	Price /Book Value
OP	Percentage change in Operating Profit

The seven independent variables were considered for final analysis is given in Table no. 3

Empirical Results and Analysis

The estimated results of the Multi logistic regression model of the stock price return performance on the whole sample are summarized in Table 5. The final Multi logistic regression equations are estimated by using the maximum likelihood estimation for classifying company are

Poor performance w.r.t good performance ($Y_{P/G}$) = g(1)=4.31NS – 3.824 OP + 0.033 EPS -0.007 BV – 0.196 PEBV + 0.03 PECEPS + 0.035 PBIDTS – 0.421
Average performance w.r.t good performance ($Y_{AV/G}$) =g(2)= - 0.91NS – 0.282OP + 0.035 EPS – 0.007 BV – 0.051 PEBV + 0.057PECEPS + 0.03 PBIDTS – 0.706
From our study we have got
log p/1-p =$A+B_1X_1 + \ldots\ldots\ldots.+B_kX_k$
log(g(1)) =$A_1 +B_{11} X_1+\ldots\ldots\ldots\ldots\ldots+ B_{1k}X_k$
log((g(2))=$A_2 +B_{12}X_1+\ldots\ldots\ldots\ldots.+B_{2k}X_k$
log(g(3))=log1=0
Using the formula of Multilogistic regression we have got

$$f(1) = \frac{g(1)}{g(1)+g(2)+1} = \frac{e^{A_1+B_{11}X_1+\ldots+B_{1k}X_k}}{e^{A_1+B_{11}X_1+\ldots+B_{1k}X_k}+e^{A_2+B_{21}X_1+\ldots+B_{2k}X_k}+1}$$

$$f(2) = \frac{g(2)}{g(1)+g(2)+1} = \frac{e^{A_2+B_{21}X_1+\ldots+B_{2k}X_k}}{e^{A_1+B_{11}X_1+\ldots+B_{1k}X_k}+e^{A_2+B_{21}X_1+\ldots+B_{2k}X_k}+1}$$

$$f(3) = \frac{g(3)}{g(1)+g(2)+1} = \frac{1}{e^{A_1+B_{11}X_1+\ldots+B_{1k}X_k}+e^{A_2+B_{21}X_1+\ldots+B_{2k}X_k}+1}$$

Classification Accuracy

The following classification table helps to assess the performance of the model by cross tabulating the observed response categories with the predicted response categories.

CLASSIFICATION TABLE-4

	Predicted			
Observed	POOR	AVERAGE	GOOD	Percent Correct
POOR	19	15	3	51.40%
AVERAGE	9	37	6	71.20%
GOOD	11	7	11	37.90%
Overall Percentage	33.10%	50.00%	16.90%	56.80%

The above table shows the comparison of the observed and the predicted performance of the companies and to the extent that it can be correctly predicted. POOR companies can be classified

51.40% correctly, AVERAGE companies classified at 71.2% while 37.9% of GOOD companies can be properly classified. The overall prediction is 56.80% correct. Here we have 3*3 matrix with 9 cells as, we see from the above table. Diagonal 3 cells are classified and remaining 6 cells are misclassified. So the probability of classified cells is 33.33% but our model equation has predicted 56.8% correctly classified. So our prediction based on this model is much above 33.33%. So it can be used for prediction with higher accuracy.

Tests of Goodness of Fit

The Multinomial Logistic Regression procedure reports Pearson and Deviance goodness-of-fit statistics. The goodness-of-fit table presents two tests of the null hypothesis that the model adequately fits the data. If the null is true, the Pearson and deviance statistics have a chi-square distribution with the displayed degrees of freedom. If the significance of the test is small (i.e., less than 0.05) then the model does not adequately fit the data.

Table-5
Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	223.638	212	0.278
Deviance	216.631	212	0.399

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Our significant values with respect to Pearson and Deviance procedure are 0.278 and 0.399 that is >0.05 so our model to be considered as reasonably good.

Test of Appropriateness of the Model

Table-6
Model Fitting Information

	Model Fitting Criteria	Likelihood Ratio Tests		
Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	248.282			
Final	220.789	27.493	14	0.017

The above table contains the model fitting information. A likelihood ratio test shows whether the model fits the data better than a null model. The chi-square statistic is the difference between the

-2 log-likelihoods of the Null and Final models. Since the significance level of the test is less than 0.05, you can conclude the Final model is outperforming the Null. For each effect, the -2 log-likelihood is computed for the reduced model; that is, a model without the effect. The above table shows the significant value of 0.017.

Test of variance of the Model

Table-7
Pseudo R-Square

Cox and Snell	0.208
Nagelkerke	0.236
McFadden	0.109

In linear regression, the r-square statistic measures the proportion of the variation in the response that is explained by the model .The r-square statistic cannot be exactly computed for multinomial logistic regression models, so these approximations are computed instead
Larger pseudo r-square statistics indicate that more of the variation is explained by the model, to a maximum of 1.

Test of significance of parameters

Table-8
Likelihood Ratio Tests

	Model Fitting Criteria	Likelihood Ratio Tests		
Effect	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	221.443	0.653	2	0.721
NS	227.298	6.508	2	0.039
EPS	225.746	4.956	2	0.084
BV	225.242	4.452	2	0.108
PEBV	222.196	1.406	2	0.495
PECEPS	222.757	1.967	2	0.374
PBIDTS	225.665	4.876	2	0.087
OP	232.025	11.235	2	0.004

The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.
The likelihood ratio tests check whether each effect contributes to the model. The -2 log-likelihood is computed for the reduced model, that is, one without the effect .The chi-square is the difference in the -2 log-likelihood between the reduced model and the final model. If the

significance of the test is small (i.e., less than 0.10) then the effect contributes to the model. Our analysis shows above that the significant values of the ratios are less than (0.10) excluding PEBV and PECEPS. But from the domain of the financial management these two ratios too contribute towards predicting the valuation of the shares of the companies.

Table-9
Parameter Estimates

Perfa		B	Std. Error	Wald	Df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
								Lower Bound	Upper Bound
POOR	Intercept	-0.421	0.945	0.199	1	0.656			
	NS	4.31	2.286	3.554	1	0.059	74.40	0.843	6568.92
	OP	-3.824	1.489	6.591	1	0.01	0.022	0.001	0.405
	EPS	0.033	0.019	3.035	1	0.081	1.034	0.996	1.073
	BV	-0.007	0.004	3.143	1	0.076	0.993	0.985	1.001
	PEBV	-0.196	0.173	1.276	1	0.259	0.822	0.585	1.155
	PECEPS	0.03	0.05	0.372	1	0.542	1.031	0.935	1.136
	PBIDTS	0.035	0.018	3.961	1	0.047	1.036	1.001	1.072
AVEGE	Intercept	-0.706	0.879	0.646	1	0.422			
	NS	-0.91	2.071	0.193	1	0.66	0.403	0.007	23.292
	OP	-0.282	0.777	0.132	1	0.717	0.754	0.164	3.459
	EPS	0.035	0.017	4.144	1	0.042	1.035	1.001	1.07
	BV	-0.007	0.004	3.715	1	0.054	0.993	0.986	1
	PEBV	-0.051	0.137	0.14	1	0.709	0.95	0.727	1.242
	PECEPS	0.057	0.042	1.87	1	0.171	1.059	0.976	1.149
	PBIDTS	0.03	0.017	3.097	1	0.078	1.031	0.997	1.066
a. The reference category is: GOOD.									

Parameter estimates, their standard errors, significance tests, and confidence intervals are provided for all model parameters. The Wald statistic is the square of the ratio of the parameter estimate to its standard deviation. If the significance of the statistic is small (i.e., less than 0.10) then the parameter is useful to the model. Parameters with significant negative coefficients decrease the likelihood of that response. Parameters with positive coefficients increase the likelihood of that response category. The estimated correlation between each pair of parameters is displayed. Missing values in the matrix mean that one or both of the parameters is redundant. The estimated covariance between each pair of parameters is displayed. Zero values in the matrix mean that one or both of the parameters is redundant. This cross-tabulation of the observed response categories with the predicted response categories helps you to assess the predictive performance of your model. For each case, the predicted response category is chosen by selecting the category with the highest model-predicted probability. Cells along the diagonal represent numbers of correct predictions. Cells off the diagonal represent numbers of incorrect predictions.

Validation of the Model

Model validation requires checking the model against independent data to ensure its prediction capability. Typically, the steps of model fitting start with collecting an independent data set and validating the results on it. To validate the developed model in this study, 101 test samples have been considered as given in the Annexure II. The result of validation is given in the Annexure III which shows the evaluation of the independent data set and the overall prediction is 58.41% correct. On the above data set "C" denotes Classified and "UC" is unclassified.

Conclusion

This study has employed the Multi Logistic Regression Model to determine the factors which significantly affect the performance of the company in the stock market. Multi Logistic regression method helps the investor to form an opinion about the shares to be invested. It may be observed that seven financial ratios i.e. Percentage change in Net Sales , Book Value , PBIDT/Sales and Earnings per Share ,PEBV, OP, PECEPS can classify up to 56.80.% into three categories Good, Average or Poor. The prediction rate of 56.80 is good, as we have 3*3 matrix with 9 cells and diagonal 3 cells are classified and remaining 6 cells are misclassified. So the probability of classified cells is 33.33% but our model equation has predicted 56.8% correctly classified. So our prediction based on this model is much above 33.33%. So it can be used for prediction with higher accuracy.

When evaluated from investors' point of view, it is concluded that it is possible to predict outperforming share by examining these seven ratios. Various methods are available for data processing for analysis, but in this study it has been identified that ratio methods have the capability to reveal maximum information content, if variables are chosen very carefully with regard to the purpose at hand. Ratios enjoy remarkable simplicity and in spite of problem of multi –collinearity, the information revealed by them is so direct to a particular decision-control situation that movements of ratio give a picturesque representation of the movement of an actual business process.

In this study data, for 12 months have been taken into consideration and at the end of 12th month, stock share prices and variances were compared with the previous year and performance was determined. This study uses only financial ratios as only factor affecting share prices. There may various economic and management factor that may also influence the share prices. McConnell, Haslem and Gibson (1986) have identified that qualitative data can provide additional information to forecast stock price performance more accurately.

Further studies can use qualitative data for improving the forecasting ability. In this study, only Multi logistic regression is considered to build the model. Therefore, for further development, this study proposes to investigate and employ the various approaches like genetic algorithm, rough set approach to increase the prediction ratio.

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Annexure I- Sample Data Set (118 Observations)

Year	Perf	Company	NS	OP	EPS	BV	PEBV	PECEPS	PBIDTS
2008	1	Tata motor	0.04	0.04	50.52	202.68	3.08	9.24	11.11
2007	1	Tata motor	0.34	0.23	47.1	177.57	4.1	11.68	11.16
2006	1	Tata motor	0.17	0.24	37.59	143.93	6.48	18.22	12.11
2005	0	Tata motor	0.33	0.24	32.44	113.64	3.64	9.22	11.51
2008	1	Tata Steel	0.12	0.2	61.06	298.7	2.32	9.56	39.79
2007	2	Tata Steel	0.15	0.18	69.95	240.22	1.87	5.35	37.1
2006	1	Tata Steel	0.08	0.01	61.51	176.19	3.04	7.1	36.11
2005	0	Tata Steel	0.33	0.75	60.91	127.51	3.14	5.56	38.72
2008	1	TCS	0.24	0.21	43.69	111.43	7.28	16.76	29.49
2007	2	TCS	0.33	0.35	36.66	82.35	14.95	30.65	30.23
2006	2	TCS	0.4	0.48	53.63	114.64	16.7	32.5	29.69
2008	1	Sterlite	0.09	0.15	12.75	185.82	3.84	48.51	10.48
2007	2	Sterlite	0.6	0.32	13.48	79.82	5.87	29.52	9.94
2006	2	Sterlite	0.87	2.03	44.84	366.97	4.77	31.06	11.99
2005	0	Sterlite	0.35	-0.3	9.25	324.09	2.21	36.41	7.4
2008	2	Tata Power	0.26	0.34	38.26	352.27	3.33	22.79	24.15
2007	0	Tata Power	0.03	-0.1	33.59	291.77	1.75	10.54	22.62
2006	2	Tata Power	0.16	-0.09	29.66	267.76	2.16	13.25	26.06
2005	1	Tata Power	-0.07	-0.03	26.8	248.36	1.44	7.95	33.27
2008	0	Satyam	0.31	0.22	24.99	109.71	3.6	14.59	25.63
2007	2	Satyam	0.34	0.09	20.77	86.65	5.43	20.7	27.47
2006	1	Satyam	0.34	0.62	37.22	133.57	6.36	20.71	33.91
2005	0	Satyam	0.36	0.25	22.85	100.77	4.05	15.65	28.05
2008	1	SBI	0.31	0.45	103.94	776.48	2.06	13.94	66.15
2007	0	SBI	0.03	0.08	83.91	594.69	1.67	10.41	59.83
2006	2	SBI	0.1	0.09	81.77	525.25	1.84	10.05	56.99
2005	0	SBI	0.04	-0.01	80.01	457.38	1.44	6.97	57.62
2008	1	Reliance Industries	0.18	0.41	131.97	542.83	4.17	13.7	20.78
2007	2	Reliance Industries	0.33	0.37	84.28	439.67	3.11	11.51	17.34
2006	1	Reliance Industries	0.22	0.05	63.7	324.11	2.46	9.04	16.81
2005	1	Reliance Industries	0.3	0.3	53.3	270.43	2.02	6.82	19.49
2008	1	Reliance Energy	0.1	0.24	44.97	430.21	2.91	22.99	26.45
2007	0	Reliance Energy	0.46	0.03	34.16	374.19	1.32	11.09	23.62
2006	2	Reliance Energy	-0.05	0.26	29.92	327.54	1.87	13.2	33.42

2005	2	Reliance Energy	0.18	0.3	27.4	267.3	1.98	11.5	25.3
2008	0	ONGC	0.06	0.05	72.65	330.16	2.97	12.39	44.38
2007	1	ONGC	0.18	0.05	68.4	289.51	3.03	11.57	44.45
2006	1	ONGC	0.03	0.19	94.89	378.42	3.46	11.85	49.93
2005	0	ONGC	0.44	0.42	85.61	328.53	2.69	9.87	43.35
2008	1	NTPC	0.14	0.1	8.4	65.5	3.01	17.92	38.38
2007	2	NTPC	0.22	0.22	7.85	59.73	2.51	14.44	39.51
2006	2	NTPC	0.18	0.09	6.67	55.06	2.43	14.65	39.65
2005	0	NTPC	0.2	-0.13	6.72	51.07	1.68	9.43	43.06
2008	2	Maruti	0.22	0.21	59.03	291.19	2.85	10.54	14.89
2007	2	Maruti	0.17	0.26	53.29	237.16	3.46	13.08	15.05
2006	1	Maruti	0.11	0.14	40.65	188.67	4.63	17.3	13.93
2005	2	Maruti	0.21	0.37	29.25	151.52	2.78	9.34	13.48
2008	2	Mahindra&Mahindra	0.15	0.05	44.54	181.44	3.83	12.76	13.47
2007	1	Mahindra&Mahindra	0.21	0.24	43.1	148.72	5.25	15.03	14.73
2006	1	Mahindra&Mahindra	0.21	0.43	35.26	124.06	5.05	14.31	14.35
2005	0	Mahindra&Mahindra	0.3	0.36	44.02	176.64	2.81	8.22	12.14
2008	1	L&T	0.41	0.53	71.73	325.95	9.28	38.56	13.98
2007	1	L&T	0.2	0.38	47.65	202.67	7.99	30.38	12.83
2006	2	L&T	0.12	0.11	70.58	335.57	7.25	31.04	11.08
2005	2	L&T	0.35	0.54	71.94	256.98	3.87	12.65	11.18
2008	0	Jaiprakash	0.06	0.05	72.65	330.16	2.97	12.39	44.38
2007	0	Jaiprakash	0.18	0.05	68.4	289.51	3.03	11.57	44.45
2006	2	Jaiprakash	0.03	0.19	94.89	378.42	3.46	11.85	49.93
2005	1	Jaiprakash	0.44	0.42	85.61	328.53	2.69	9.87	43.35
2008	0	Infosys	0.19	0.23	72.5	235.84	6.06	17.43	36.2
2007	1	Infosys	0.46	0.47	64.35	195.14	10.31	27.74	35.15
2006	0	Infosys	0.32	0.26	81.41	249.89	11.93	30.98	34.85
2005	1	Infosys	0.44	0.47	68.96	194.15	11.6	28.55	36.41
2008	1	ITC	0.11	0.17	7.68	31.85	6.48	23.32	23.58
2007	0	ITC	0.19	0.2	6.65	27.59	5.45	19.75	22.31
2006	1	ITC	0.22	0.06	5.58	23.97	8.13	30.15	22.05
2005	1	ITC	0.13	0.31	83.92	315.63	4.26	13.92	25.4
2008	0	ICICI	0.37	0.42	36.02	417.64	1.84	18.68	69.68
2007	1	ICICI	0.5	0.6	32.88	270.35	3.16	21.91	67.23
2006	0	ICICI	0.5	0.42	27.35	249.55	2.36	17.15	62.67

2005	2	ICICI	0.07	-0.01	25.99	170.34	2.31	11.56	66.23
2008	1	HDFC	0.5	0.52	81.53	420.64	5.67	29.03	96.63
2007	1	HDFC	0.38	0.39	58.33	219.42	6.93	25.76	95.86
2006	1	HDFC	0.26	0.26	47.58	179.05	7.46	27.65	95.02
2005	0	HDFC	0.11	0.11	39.19	155.87	4.66	18.19	94.81
2008	1	HDFC BANK	0.5	0.5	43.42	324.39	4.07	25.84	52.24
2007	1	HDFC BANK	0.45	0.54	34.55	201.42	4.71	22.92	52.42
2006	0	HDFC BANK	0.49	0.41	27.04	169.24	4.57	23.63	49.22
2005	0	HDFC BANK	0.26	0.15	20.84	145.86	3.73	21.35	51.8
2008	1	Hindalco	0.06	-0.09	23.01	141.02	1.17	5.93	18.71
2007	0	Hindalco	0.61	0.51	24.34	119.03	1.09	4.4	21.82
2006	2	Hindalco	0.19	0.12	16.49	97.46	1.87	8.4	23.34
2005	2	Hindalco	0.57	0.46	140.43	826.32	1.57	6.8	24.65
2008	0	Bharti Airtel	0.44	0.48	32.9	106.34	7.77	16.66	41.72
2007	1	Bharti Airtel	0.59	0.79	21.27	60.19	12.68	22.66	40.7
2006	1	Bharti Airtel	0.42	0.4	10.62	38.71	10.67	21.97	36.23
2008	1	Grasim	0.21	0.38	239.03	887.12	2.9	9.28	31.43
2007	0	Grasim	0.26	0.66	163.68	679.19	3.08	10.54	27.64
2006	1	Grasim	0.06	-0.07	91.36	543.01	3.79	16.71	20.96
2005	0	Grasim	0.17	0.15	94.34	471.65	2.57	9.68	23.98
2008	1	BHEL	0.14	0.18	55.82	220.1	9.34	33.23	21.92
2007	0	BHEL	0.29	0.41	94.86	359.06	6.3	21.32	21.31
2006	1	BHEL	0.4	0.52	66.57	298.31	7.53	29.33	19.46
2005	0	BHEL	0.19	0.48	37.86	246.24	3.12	16.4	17.82
2008	0	Sun Pharma	0.39	0.6	47.16	203.15	6.06	24.69	34.68
2007	1	Sun Pharma	0.32	0.29	31.57	126.58	8.33	31.03	30.21
2006	1	Sun Pharma	0.39	0.47	24.06	78.8	10.99	33	31.04
2005	0	Sun Pharma	0.26	0.15	15.94	59.51	7.92	26.62	29.34
2008	1	SAIL	0.16	0.18	17.62	55.84	3.31	8.96	28.17
2007	1	SAIL	0.21	0.49	14.54	41.92	2.72	6.53	27.78
2006	0	SAIL	0.02	-0.34	9.44	30.51	2.73	6.74	22.58
2005	1	SAIL	0.33	1.37	16.06	24.95	2.52	3.35	34.8
2008	0	Dr Reddy	-0.15	-0.51	27.62	286.11	2.07	15.86	22.05
2007	2	Dr Reddy	0.92	2.88	69.45	260.44	2.79	9.4	38.35
2006	2	Dr Reddy	0.29	1.67	26.82	294.93	4.82	34.36	18.99
2005	0	Dr Reddy	-0.07	-0.61	7.85	271.05	2.73	37.07	9.19
2008	2	Wipro	0.28	0.14	19.94	79.05	5.38	18.44	22.89

2007	2	Wipro	0.34	0.34	18.61	63.86	8.74	26.49	25.75
2006	1	Wipro	0.41	0.35	13.47	45.03	12.4	35.99	25.67
2005	0	Wipro	0.4	0.57	20.55	69.54	9.65	28.94	26.77
2008	1	Asian Paints	0.21	0.32	36.23	96.8	12.4	29.48	15.18
2007	1	Asian Paints	0.21	0.31	26.51	77.57	9.86	24.55	13.86
2006	1	Asian Paints	0.19	0.1	17.72	64.87	9.93	28.67	12.77
2005	0	Asian Paints	0.15	0.13	16.81	59.66	6.56	17.96	13.75
2008	0	Shree_Cement	0.51	0.42	73.38	193.11	5.59	5.12	36.84
2007	1	Shree_Cement	0.96	2.09	49.96	130.47	7.07	5.29	39.3
2006	2	Shree_Cement	0.14	0.17	4.58	85.05	10.51	17.3	24.9
2005	1	Shree_Cement	0.19	0.3	7.78	83.09	4.08	7.87	24.25

Annexure II- Validation Sample

YEAR	COMPANY	NS	OP	EPS	BV	PEBV	PECEPS	PBIDTS
2010	JSW	0.281789	0.35857	78.99	380.01	3.25	9.95	24.89
2009	JSW	0.201948	0.29999	16.99	309.19	0.75	4.6	15.43
2008	JSW	0.358348	-0.3612	66.5	297.82	2.75	8.7	29.03
2007	JSW	0.366939	1.06807	54.69	235.25	2.1	6.42	30.33
2010	JINDAL	-0.0666	0.018	15.84	72.2	9.73	32.9	34.88
2009	JINDAL	0.38193	0.23031	99.32	348.23	3.45	9.44	31.98
2008	JINDAL	0.56809	0.51058	79.64	241.84	8.57	19.02	35.92
2007	JINDAL	0.3553	0.38619	225.36	804.35	2.95	7.1	37.29
2010	LUPIN	0.24614	0.41322	70.7	284.52	5.71	20.34	22.33
2009	LUPIN	0.12724	-0.1063	48.22	166.06	4.15	12.26	19.69
2008	LUPIN	0.28636	0.3497	52.31	160.46	3.08	8.35	24.83
2007	LUPIN	0.22145	0.596177	36.75	110.58	5.48	14.24	23.67
2010	IND.CEM	0.068135	-0.0588	11.2	114.86	1.15	7.01	22.12
2009	IND.CEM	0.08008	-0.1096	14.96	105	1.01	4.78	25.1
2008	IND.CEM	0.36147	0.4541	22.28	92.13	2.03	6.97	30.45
2007	IND.CEM	0.42708	1.67988	20.64	62.92	2.57	6.4	28.51
2010	IOL	-0.117	0.683297	40	208.21	1.43	5.57	6.49
2009	IOL	0.21999	-0.219	23.44	368.82	1.05	8.14	3.41
2008	IOL	0.1344	-0.0158	57.75	344.58	1.29	5.54	5.32
2007	IOL	0.235866	0.46694	61.11	298.22	1.34	4.8	6.13
2010	B.FORGE	-0.1012	0.09932	5.53	68.63	3.69	19.63	23.54
2009	B.FORGE	-0.0858	-0.3644	4.47	66.77	1.47	8.77	19.25
2008	B.FORGE	0.16251	0.183825	11.65	66.16	4.04	14.94	27.68
2007	B.FORGE	0.20552	0.22384	10.18	59.13	5.33	21.48	27.19
2010	B.PETRO	-0.09555	0.08793	40.52	361.97	1.43	6.9	3.51
2009	B.PETRO	0.19483	-0.028	19.48	335.46	1.12	7.65	2.92
2008	B.PETRO	0.13245	0.03884	43.46	322.97	1.27	5.57	3.59
2007	B.PETRO	0.26192	1.95588	47.4	284.16	1.06	4.17	3.91
2010	CEN.CMT	0.143008	0.31165	35.57	188.98	2.69	8.38	17.64
2009	CEN.CMT	0.087567	-0.0059	24.66	158.91	1.38	4.44	15.37
2008	CEN.CMT	0.102677	0.17331	29.27	138.3	5.27	14.51	16.81
2007	CEN.CMT	0.19322	0.45241	28.8	113.53	4.8	12.32	15.8
2010	CIPLA	0.07767	0.37383	13.14	73.55	4.58	22.18	28.06
2009	CIPLA	0.22822	0.137019	9.65	55.86	3.93	18.93	22.01
2008	CIPLA	0.15719	0.05379	8.68	48.2	4.56	21.59	23.78
2007	CIPLA	0.17005	0.14443	8.25	41.52	5.68	24.59	26.11
2010	ASOK.LE	0.18442	0.55475	2.94	17.56	3.18	12.49	10.59
2009	ASOK.LE	-0.2579	-0.3864	1.26	15.85	1.14	6.96	8.07
2008	ASOK.LE	0.07862	0.13764	3.27	15.99	2.21	7.66	9.76
2007	ASOK.LE	0.37356	0.266512	3.12	14.14	2.72	9.03	9.25

2010	ESAR.OL	0.014	0.61135	0.24	28.9	4.79	22.24	4.57
2010	C.GREAV	0.12655	0.428173	9.41	27.28	9.57	25.55	17.61
2009	C.GREAV	0.16368	0.23353	10.49	33.48	3.68	10.5	13.89
2008	C.GREAV	0.16551	0.4672	8.29	24.99	11.01	29.27	13.1
2007	C.GREAV	0.16551	0.42202	5.07	17.98	11.09	32.2	10.41
2010	GAIL	0.03937	0.0741	23.5	132.43	3.09	14.67	20.53
2009	GAIL	0.31401	0.07645	20.91	116.44	2.1	9.64	19.86
2008	GAIL	0.12295	0.271932	29.06	153.79	2.76	11.86	24.25
2007	GAIL	0.11229	-0.104	26.76	134.72	1.96	7.88	21.41
2010	HUNILEV	-0.1581	-0.0654	9	11.84	20.16	24.24	16.54
2009	HUNILEV	0.47061	0.29277	8.14	9.45	25.21	21.51	14.9
2008	HUNILEV	0.12882	0.07012	7.21	6.61	32.36	27.26	16.95
2007	HUNILEV	0.08847	0.31743	7.57	12.34	17.55	26.55	17.88
2010	H.PETRO	-0.12486	0.11038	36.4	340.93	0.93	4.5	3.62
2009	H.PETRO	0.172886	0.38552	16.07	316.53	0.85	5.98	2.85
2008	H.PETRO	0.157237	-0.1191	32.97	311.59	0.82	4.4	2.41
2007	H.PETRO	0.260208	1.68773	43.47	283.19	0.87	3.84	3.17
2010	IVRCL	0.10261	0.14648	7.78	69.3	2.39	16.86	10.83
2009	IVRCL	0.34747	0.194395	16.69	135.41	0.9	6.01	10.42
2008	IVRCL	0.57604	0.64377	15.53	120.05	3.34	22.3	11.75
2007	IVRCL	0.54228	0.75036	10.74	101.41	2.88	23.54	11.27
2010	T.TEA	0.24708	0.75578	60.16	332.47	2.95	15.76	33.21
2009	T.TEA	0.19989	0.07645	22.95	287.43	2.04	23.73	23.59
2008	T.TEA	0.07615	0.27193	44.64	288.19	2.86	17.81	40.68
2007	T.TEA	0.08904	-0.104	49.26	257.81	2.36	11.6	39.22
2010	B.PAINT	0.07922	0.31034	3.29	18.07	3.25	14.47	11.01
2009	B.PAINT	0.10964	0.01897	2.68	12.99	2.68	10.48	9.06
2008	B.PAINT	0.1509	0.15404	2.8	10.91	3.31	10.67	9.87
2007	B.PAINT	0.184275	0.12605	2.45	8.61	4.25	12.15	9.84
2010	PIDILITE	0.059863	0.637188	5.46	18.55	6.16	17.92	20.17
2009	PIDILITE	0.12041	-0.109	5.48	28.99	2.91	11.49	13.06
2008	PIDILITE	0.319534	0.44568	7.14	25.27	5.26	15.33	16.42
2007	PIDILITE	0.23547	0.19002	4.5	19.33	5.85	19.84	14.99
2010	UNITEC	0.03358	-0.3676	2.2	32.41	2.26	33.02	55.85
2009	UNITEC	-0.3401	-0.0445	4.53	17.61	1.98	7.6	91.27
2008	UNITEC	0.11987	0.145431	6.31	13.21	20.9	43.42	63.03
2007	UNITEC	2.832803	9.40085	12.03	14.3	27.09	32.04	61.62
2010	TVS	0.1673	0.27932	3.52	36.43	2.26	10.48	5.43
2009	TVS	0.08833	0.40416	1.19	34.11	0.66	4.1	4.95
2008	TVS	-0.1766	-0.3376	1.22	34.59	1.01	6.72	3.84
2007	TVS	0.19875	-0.2465	2.68	34.07	1.75	9.36	4.77

2010	INFOSYS	0.043229	0.12402	96.92	383.9	6.81	23.56	39.4
2009	INFOSYS	0.29499	0.30826	97.74	311.35	4.25	12.05	36.57
2008	INFOSYS	0.190052	0.22544	72.5	235.84	6.06	17.43	36.2
2007	INFOSYS	0.456469	0.46917	64.35	195.14	10.31	27.74	35.15
2010	HINDALC	0.0463	-0.1247	9.79	145.83	1.25	13.67	15.71
2009	HINDALC	-0.0568	-0.05713	12.89	139.69	0.37	3.11	18.78
2008	HINDALC	0.05218	-0.09437	23.01	141	1.17	5.93	18.78
2007	HINDALC	0.61465	0.510007	24.34	119.03	1.09	4.4	21.82
2010	WIPRO	0.064476	0.490499	32.49	120.51	5.87	19.4	27.72
2009	WIPRO	0.22396	0.058304	19.62	85.42	2.87	10.55	19.8
2008	WIPRO	0.283432	0.140946	19.94	79.05	5.38	18.44	22.89
2007	WIPRO	0.34045	0.344632	18.61	63.86	8.74	26.49	25.75
2010	MAHIND	0.388804	1.260391	35.58	137.96	3.95	12.94	16.74
2009	MAHIND	0.128053	-0.1386	30.6	192.34	1.99	9.28	10.29
2008	MAHIND	0.150472	0.051666	44.54	181.27	3.84	12.76	13.47
2007	MAHIND	0.210109	0.242305	43.1	148.59	5.25	15.03	14.73
2010	SAIL	-0.09889	0.084525	15.8	80.66	3.12	13.23	27.04
2009	SAIL	0.059505	-0.15508	14.5	68.15	1.42	5.47	22.47
2008	SAIL	0.164723	0.181368	17.62	55.84	3.31	8.96	28.17
2007	SAIL	0.207879	0.485778	14.54	41.92	2.72	6.53	27.78

Annexure- III- Validation Result

Year	Company	f(1)	f(2)	f(3)		performance	Result
2010	JSW	0.290984	0.387933	0.321083	1	AVG	UC
2009	JSW	0.128373	0.117696	0.753931	2	GOOD	C
2008	JSW	0.913247	0.054793	0.03196	0	POOR	C
2007	JSW	0.06507	0.48966	0.44527	1	AVG	UC
2010	JINDAL	0.080714	0.791552	0.127734	1	AVG	C
2009	JINDAL	0.602342	0.308522	0.089137	0	POOR	C
2008	JINDAL	0.376554	0.505205	0.118241	1	AVG	C
2007	JINDAL	0.452276	0.505862	0.041862	1	AVG	C
2010	LUPIN	0.165082	0.60615	0.228768	1	AVG	C
2009	LUPIN	0.506827	0.34147	0.151703	0	POOR	C
2008	LUPIN	0.37461	0.418736	0.206654	1	AVG	UC
2007	LUPIN	0.098394	0.5982	0.303406	1	AVG	C
2010	IND.CEM	0.451511	0.252499	0.29599	0	POOR	UC
2009	IND.CEM	0.556132	0.223553	0.220316	0	POOR	C
2008	IND.CEM	0.396765	0.328563	0.274672	0	POOR	UC

2007	IND.CEM	0.009224	0.446657	0.544118	2	GOOD	C
2010	IOL	0.01678	0.39212	0.591099	2	GOOD	C
2009	IOL	0.400761	0.065781	0.533459	2	GOOD	C
2008	IOL	0.364126	0.19645	0.439425	2	GOOD	UC
2007	IOL	0.168218	0.292486	0.539295	2	GOOD	C
2010	B.FORGE	0.124103	0.586848	0.289048	1	AVG	C
2009	B.FORGE	0.537848	0.250245	0.211907	0	POOR	C
2008	B.FORGE	0.297258	0.439876	0.262866	1	AVG	UC
2007	B.FORGE	0.257748	0.504845	0.237407	1	AVG	C
2010	B.PETRO	0.072427	0.193434	0.734139	2	GOOD	C
2009	B.PETRO	0.234067	0.085419	0.680514	2	GOOD	C
2008	B.PETRO	0.260978	0.168873	0.570149	2	GOOD	C
2007	B.PETRO	0.000649	0.178596	0.820755	2	GOOD	C
2010	CEN.CMT	0.192617	0.377033	0.430349	2	GOOD	UC
2009	CEN.CMT	0.392675	0.245263	0.362062	0	POOR	UC
2008	CEN.CMT	0.183881	0.462943	0.353175	1	AVG	UC
2007	CEN.CMT	0.125226	0.466935	0.407839	1	AVG	UC
2010	CIPLA	0.107777	0.640773	0.251451	1	AVG	C
2009	CIPLA	0.386779	0.386483	0.226738	0	POOR	UC
2008	CIPLA	0.355615	0.446486	0.197898	1	AVG	UC
2007	CIPLA	0.263504	0.537245	0.199251	1	AVG	C
2010	ASOK.LE	0.094727	0.411372	0.493901	2	GOOD	UC
2009	ASOK.LE	0.347926	0.350689	0.301385	1	AVG	UC
2008	ASOK.LE	0.254702	0.336037	0.409261	2	GOOD	UC
2007	ASOK.LE	0.4366	0.218377	0.345023	0	POOR	UC
2010	ESAR.OL	0.023291	0.506769	0.469939	1	AVG	C
2010	C.GREAV	0.048118	0.634571	0.317311	1	AVG	C
2009	C.GREAV	0.244161	0.385384	0.370455	1	AVG	UC
2008	C.GREAV	0.036551	0.627927	0.335521	1	AVG	C
2007	C.GREAV	0.039215	0.632993	0.327792	1	AVG	C
2010	GAIL	0.256812	0.449793	0.293394	1	AVG	UC
2009	GAIL	0.604278	0.192089	0.203633	0	POOR	C
2008	GAIL	0.223689	0.447607	0.328704	1	AVG	UC
2007	GAIL	0.55002	0.248105	0.201875	0	POOR	C
2010	HUNILEV	0.013634	0.622772	0.363594	1	AVG	C
2009	HUNILEV	0.02881	0.34176	0.62943	2	GOOD	C
2008	HUNILEV	0.004232	0.442117	0.55365	2	GOOD	C
2007	HUNILEV	0.017035	0.60193	0.381035	1	AVG	C
2010	H.PETRO	0.062741	0.182692	0.754567	2	GOOD	C
2009	H.PETRO	0.056047	0.090635	0.853318	2	GOOD	C
2008	H.PETRO	0.373834	0.108606	0.51756	2	GOOD	C

2007	H.PETRO	0.001613	0.16632	0.832067	2	GOOD	C
2010	IVRCL	0.249596	0.395919	0.354485	1	AVG	UC
2009	IVRCL	0.485823	0.155968	0.358209	0	POOR	UC
2008	IVRCL	0.294019	0.308178	0.397803	2	GOOD	UC
2007	IVRCL	0.203402	0.356227	0.440371	2	GOOD	UC
2010	T.TEA	0.080806	0.545552	0.373641	1	AVG	C
2009	T.TEA	0.357965	0.29508	0.346955	0	POOR	UC
2008	T.TEA	0.191767	0.554676	0.253557	1	AVG	C
2007	T.TEA	0.553081	0.315816	0.131103	0	POOR	C
2010	B.PAINT	0.135557	0.456486	0.407957	1	AVG	UC
2009	B.PAINT	0.360488	0.307647	0.331865	0	POOR	UC
2008	B.PAINT	0.277428	0.337898	0.384674	2	GOOD	UC
2007	B.PAINT	0.299294	0.330622	0.370085	2	GOOD	UC
2010	PIDILITE	0.03088	0.587966	0.381153	1	AVG	C
2009	PIDILITE	0.49461	0.265616	0.239775	0	POOR	UC
2008	PIDILITE	0.197259	0.411142	0.391598	1	AVG	UC
2007	PIDILITE	0.265353	0.427487	0.30716	1	AVG	UC
2010	UNITEC	0.679218	0.299803	0.020979	0	POOR	C
2009	UNITEC	0.191293	0.758805	0.049902	1	AVG	C
2008	UNITEC	0.027165	0.903815	0.06902	1	AVG	C
2007	UNITEC	4.67E-12	0.03487	0.96513	2	GOOD	C
2010	TVS	0.206042	0.314092	0.479865	2	GOOD	UC
2009	TVS	0.118616	0.282971	0.598413	2	GOOD	C
2008	TVS	0.365423	0.285222	0.349355	0	POOR	UC
2007	TVS	0.692052	0.125462	0.182485	0	POOR	C
2010	INFOSYS	0.159183	0.749266	0.091551	1	AVG	C
2009	INFOSYS	0.405674	0.506133	0.088192	1	AVG	C
2008	INFOSYS	0.268881	0.619569	0.11155	1	AVG	C
2007	INFOSYS	0.205503	0.676115	0.118382	1	AVG	C
2010	HINDALC	0.419764	0.260571	0.319665	0	POOR	UC
2009	HINDALC	0.306216	0.271281	0.422504	2	GOOD	UC
2008	HINDALC	0.470695	0.255819	0.273486	0	POOR	UC
2007	HINDALC	0.61563	0.141461	0.242908	0	POOR	C
2010	WIPRO	0.061644	0.691238	0.247118	1	AVG	C
2009	WIPRO	0.503334	0.274496	0.22217	0	POOR	C
2008	WIPRO	0.407551	0.383098	0.209351	0	POOR	UC
2007	WIPRO	0.20058	0.572924	0.226496	1	AVG	C
2010	MAHIND	0.021831	0.465301	0.512867	2	GOOD	C
2009	MAHIND	0.507013	0.207069	0.285918	0	POOR	C
2008	MAHIND	0.363193	0.376352	0.260456	1	AVG	UC
2007	MAHIND	0.246462	0.47499	0.278548	1	AVG	UC
2010	SAIL	0.164934	0.568018	0.267048	1	AVG	C

2009	SAIL	0.571707	0.238402	0.189892	0	POOR	C
2008	SAIL	0.357621	0.400728	0.241651	1	AVG	UC
2007	SAIL	0.199848	0.449864	0.350288	1	AVG	UC
						Classified	58.41584