Effect of Nascent Market Noise on Stock Price Movement In An Emerging Market

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Abstract

We evaluate effect of stock market noise on future stock prices in an emerging market. Three noise indicators are chosen for the purpose, viz., previous day's spread between high and low quotes of the stock, spread between opening and previous closing prices and turnover of stock. A multiple regression model is used, where dependant variable is the day's close price while the above three variables are used as independent variables. The results indicate that investors overwhelmingly use information other than these noises. We also document that the investors also use noises to a very limited extent to predict future prices. We further find that there is no significant difference of behavior of noise traders during the opposing economic conditions of the market, viz., falling and rising market conditions.

Introduction

Under Efficient Market Hypothesis (EMH) an efficient market is defined as a market where large numbers of rational profit-maximisers actively competing to predict future market prices of individual securities and where information is freely available to all participants. In such a situation, actual market prices of the individual securities reflect the impact of information of past, present and market expectation of future events. An important implication of existence of such a market is, that the future market price of the security will be dependant on future information, which by nature is unpredictable and therefore, the future market price will also be unpredictable. Ever since, the EMH has been accepted as an acknowledged theory on financial market, particularly providing theoretical basis on the movement of stock prices, it gives rise to two distinctly opposite schools of thought, one upholding the EMH while the other severely criticising it even to the brink of rejecting it and positing an alternate market efficiency mechanism. Both the groups presented a wealth of evidences to prove their contentions. Initially the evidences are overwhelmingly in favour of random nature of the stock prices, upholding the hypothesis. Subsequently the theory was challenged on the basis of evidences that pointed out that apart from fundamental information that are reflected in the security prices, there are several other variables that can be relied upon to predict the future prices of the securities. Nature of these variables is varied and also includes noises. The present paper is an attempt to understand the behaviour of the investors, who base their judgment on noises.

Motivation

One of the drivers of market efficiency is that the market does not allow investors to earn above average return without assuming above average risk. In other words, the intrinsic value of the stock would prevail ultimately. Evidences against these notions are large and widespread. There, in fact, some recognisable patterns in the past history of prices that are used by the analysts to predict the future prices. However, patterns that are discovered disappeared quickly as soon as they are reported. DeBondt and Thaler (1985) found a reversal in long term returns, i.e., the securities with low long-term returns tended to have higher future returns. Jegadeesh and Titman (1993) found that securities with higher returns during past twelve months tended to have higher returns. Basu (1983) found that earning/price (E/P) could explain cross-section of average returns on portfolio's of U.S. securities. Earlier Ball (1978) found E/P is a good proxy for explaining risk and expected returns. Similar evidence surfaced in respect of performance of mutual funds. Ippolite (1989) found that the mutual fund returns before loads but after expenses are marginally above the market line of the CAPM. Hendricks, Patel and Zeckhauser (1993) and Goetzmann amd Ibbotson (1994) found that past mutual fund returns could predict future returns. Malkiel (1995) utilizing a data on equity mutual funds during 1971 to 1991 found no consistency in fund returns and concluded that there was no reason to abandon the hypothesis that the securities markets are efficient. Pesaran and Timmermann (1995), examined the robustness of the evidence on predictability of U.S. securities returns and analysed whether this predictability could have been historically exploited by investors to earn profits in excess of a buy and hold strategy. They used recursive modeling approach and subjected their model to real time simulations on the U.S. stock returns. They found that the predictive power of various economic factors over securities returns did change over time and had a positive relation with the volatility of returns. Finally, they found that the choice of trading rule did not in any way influence the return characteristic of the securities. Another interesting research is in the area of behavioural study of the security prices following good and bad news. Campbell and Shiller (1987) and Harvey (1989) found that the link between market risk premium and market volatility was not weak and therefore, shocks to market volatility can not be said to be not sufficiently persistent to account for the predictive asymmetry of the return variances. The results point out that we can expect negative correlation between the changes in conditional beta and the unexpected component of stock returns. Chan (1988) and Ball and Kothari (1989) found evidences of predictive asymmetry in conditional betas. Glosten, Jagannathan and Runkel (1993) via an alternative approach through a model that allows quadratic functional response to news, showed that difference responses of good and bad news capture asymmetric effects. Braun, Nelson and Saulnier (1995) using exponential ARCH model documented additional evidences for predictive asymmetry. In other words, the evidences show that the market volatilities tend to rise strongly in response to bad news and fall in response to good news. There has been little research in short run stock price movement particularly using only the market price information. Lo and McKinley (1999) investigated short-run stock prices and found non zero serial correlation in the process, with the existence of a large number successive moves in the same direction. However, this study did not investigate how the investors use nascent market price information for future price discovery. As this information is not related to the fundamental performance of the firms, they are called noises. Short term momentum analysis of stock prices in an emerging market, where investors are tempted to buy stocks on the basic price information, is rare. The studies are mainly restricted to developed market and research relating to emerging market is rare. Since, emerging market is viewed as a less efficient market, an examination of the behaviour of noise traders in such market is important. It is expected that being less efficient, the future price determination in such a market would be driven by a considerable extent on noise trading rather than on fundamental information.

This study is meant to bridge this gap and we accordingly seek to investigate : (1) whether the investors use any sort of noise (market generated nascent information) to formulate their investment decision and also to evaluate characteristic of such noises (2) whether the effect of such noises is different in two opposing economic periods, i.e., during rising market and during falling market conditions. An investigation of the behaviour of the investors during these two economically opposite period is likely to reveal nature of investors' behaviour on nascent market information.

Indian Stock Market has lately emerged as an important emerging market in South-East Asia and which has also witnessed falling and rising market conditions in a short period of time. Such market trends provide us an opportunity to study the behaviour of noise traders during two economically opposite conditions. Accordingly, this research focuses on evaluating the behaviour of noise traders in Indian Stock Market during such economically opposite conditions.

Methodology

We employ a multiple regression model to understand the effect of nascent noises on the price of individual security. We restrict the characteristic noises into various meaningful combinations relating to the prices of individual security and these are previous closing price, opening, high, low and closing price of the security. The short-term investors would be influenced by intra-day volatility as given by the high and low prices, since the difference between high and low prices would be construed as an opportunity to make a short-term trading profit. The proxy for overnight volatility is given by the difference between previous closing price and opening price. The investors in order to assess the transmitted volatility of the security would use these information to formulate buy, hold and sell decisions. The direction of price movement is likely to be used to formulate their own trading strategy. A high positive rise may induce the investors to invest while a high negative slide will, in turn, induce the investors to withdraw. The proxy of the overall volatility is given by the day's turnover of the stock. A high turnover is an indication of investors' choice.

Since, our objective is to evaluate quantitative effect of noises on the stock price movement; we use the price of the security as dependant variable while noise variables are used as independent variables in the regression model. The absolute values of the stock prices as well as spread of high and low and the turnover are converted to their log values. It is observed that converting to logarithmic values; the observations are more likely to attain normal distribution. The spread of opening and previous closing price is not converted to its log since there lays the possibility of taking negative values. Since the investors would use these noises to predict future prices of the stocks, on a short-term time horizon, these indicators are calculated on the basis of previous day's prices.

The following multiple regression model is used in our study:

$$Y = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{3i} + \varepsilon$$

Subject to usual assumption like, $E(\varepsilon) = 0$ and ε are normally distributed and there are no linear dependencies in the explanatory variables, etc., and

where :

Y = log of stock price (closing price)

x_{1i} = log (Spread of high minus low quotes of previous day),

x_{2i} = Spread of opening minus previous closing price of previous day,

x_{3i} = log (Turnover of previous day)

β_0, β_1, β_2, β_3 are regression coefficients and ε is the error term.

We test the model for a possible existence of unit root. The Augmented Dickey Fuller test rejects the hypothesis for existence of unit root. Since the series are found to be stationery we do not conduct Johansen test for existence of co-integration. We also make the results White heteroskedasticity-consistent for standard errors and covariance.

Data

The stock index of National Stock Exchange of India, known as Nifty, is selected for the study. The index consists of 50 firms. Two distinct time periods conforming opposing economic periods are selected. The distressed market condition is prevalent for a long time in early 2000 and a truncated time period is taken for our study, viz., between November 1, 1999 and October 31, 2000. During this period, the market behaved in a distressed manner, with around 30% drop in market capitalization as well as the index points as the stock prices of the Information Technology companies in India crashed. The market revived in the year 2004 and continued its flourishing condition well beyond 2005 and early 2006. Accordingly we select our period of study between November 1, 2004 and October 31, 2005, to reflect the flourishing market condition. Identical calendar time periods are selected to reduce biases and to eliminate distortion that arises due to several observed effects, like, January effect, etc. All the observations are on daily basis.

For the purpose of making comparative study, we have to reduce the sample firms to 37, since the remaining 13 firms are rejected due to the fact these firms do not constitute the Nifty index during both the periods. Suitable adjustments are made to accommodate bonus shares, new share issues, stock splits etc.

Results

The results of the regression coefficient of all the firms are shown in the Table-I for the period 1999-2000 (distressed period) and those for the period 2004- 05 (flourishing period) in Table-II. From the observed values of adjusted R^2 , it is found that the cross-sectional variations of price fluctuations could be explained to a moderate extent by the variables.

Since, our basic research objective is to find out whether the investors base their investment decisions on the signals emitted by the noise, we first analyse the behaviour of regression coefficient β_0 , which indicates a factor other than noise. The coefficient is statistically significant in all cases irrespective whether it is in falling or in rising market. However its impact is different on the two opposing economic conditions. The higher impact is observed in rising market than in falling market. The impact is found to be on an average one hundred fifty percent higher in rising market when compared to falling market as the following table reveals:

	β_0	
	Falling	Rising
Minimum	2.249	2.494
Maximum	4.343	3.622
Mean	0.633	1.594
Std. Dev.	0.6407	0.4546
Significant Cases (No.)	all	all
(-) Coefficient (No.)	none	none

It is generally believed that during distressed condition, the market becomes more efficient and accordingly it is expected that the investors would not use noise for forecasting stock prices. In a falling market, the investors become more panicky and any differentially adverse news without fundamental content may lead to further fall in prices. Herd mentality comes into play in the investor's mind and he follows the trend blindly. In such a situation, even strong fundamental information may not be able to hold the prices. The investors become more sensitive on noises and overreact in its interpretation and application. As a result, the impact of noise becomes more conspicuous in falling market than in rising market. Moreover, in rising market the investors have a comparatively long term investment horizon and in such a situation fundamental information is used in a greater way than the noise.

The spread between high and low prices reflects the extremities of intra-day movement and it indicates boundaries of intra-day volatility. If the difference is high, the prices are susceptible to react more on instant market information as reflected by this variable rather than on fundamental information. Accordingly, a positive relationship would equate stock price movement with noise.

The spread between opening and previous closing prices is a differentially static price phenomenon at certain points of time. It shows the impulse of price movement during the period of no trading, that is, during a static period. The static characteristic of this noise creates lesser impact on the stock price movement with respect to high and low spread. Even if the characteristic of this noise is comparatively static, nevertheless, this noise would also have positive relationship with the stock price movements.

The turnover variable is dynamic in nature and depends entirely on investors' choice. A high turnover reflects the investors' affinity and is likely to have positive relationship with stock price movement during rising market. In falling market, high turnover might accelerate fall in prices but with market regulator's stability mechanism in place, the high turnover may not be negatively related with price movement. However, it is not always be the case, that the variables would show positive relationship. In certain cases, spread of high and low may trigger selling and with increased turnover, giving rise to negative relationship with the price movement. Such cases would however be limited in number. The regression results of the behaviour of the three variables are summarized below, which affirm the argument given above:

	β_1		β_2		β_3	
	Falling	Rising	Falling	Rising	Falling	Rising
Minimum	(-)0.101	(-)0.083	(-)0.0044	(-)0.00048	(-)0.405	(-)0.451
Maximum	0.803	0.878	0.0085	0.02473	0.223	0.171
Mean	0.222	0.1595	0.00089	0.00363	0.0266	0.0084
Std. Dev.	0.242	0.2273	0.0037	0.00795	0.1492	0.1531
Significant Cases (No.)	29	24	9	9	28	23
(-) Coefficient (No.)	6	2	3	1	8	5

Individually, the variables show different characteristics for each firm. Only in six cases, the impact of these variables is found to be nearly identical on the firms over the two time periods. Since, we experiment with previous day's price variations; it shows the speed through which noise is absorbed in the market and the accompanying effect that it brings in to the capital market. An examination of the above table reveals that the effect of noise on price discovery mechanism is only marginal. As expected, spread between high and low makes the greatest impact on future stock prices, while the spread between opening and previous closing prices makes the least impact. It is also observed that the impact of turnover on the price is substantially low. The fact that the noise does not play a significant part is additionally observed as we find that the impact of noise is not significant on approximately one-third of the total firms in the case of spread between high and low and turnover, while no significant effect is observed in respect of seventy-five percent of firms for the spread between opening and previous closing price.

It is further observed that none of the variables shows any widely different behavior between falling and rising market conditions. In agreement with our line of view, it is found that investors use noise in a differentially higher order (as conveyed by the mean) in the falling market conditions than in the rising market. The higher differences in maximum and minimum values for the variables during the two periods are due to extremities. The turnover variable shows similar behavior with respect to other two variables. The impact is differentially more in falling market than in rising market. The observed behaviour is partially explained by our earlier argument on falling market inducement for taking short-term investment decisions and the results suggest that in the process the efforts of the investors for discovery of future price are supplemented.

In financial time series data, the price discovery may need modeling the variance of error, since; the investors usually formulate their price discovery mechanism on the basis of variance. If the asset returns are unexpectedly high in either upward or downward directions, the investors would likewise increase the estimate of variance for the next period in order to enhance accuracy of their forecasting. The model for forecasting in such cases would therefore need to include forecasted variance from the preceding period and the volatility of the previous period. In such cases, ARCH and GARCH models are ideal. We have also experimented with ARCH and GARCH models and the results will be presented elsewhere. However, we find the results of GARCH are in agreement with the Least Square analysis presented here. Using GARCH and experiment with the same set of variables yields that in all cases the investors use overwhelmingly the information other than noise. The noises are found to have low impact on the future stock prices. The turnover variable emerges as the strongest and the spread between open and previous closing price being the weakest. It is also observed that during rising market the investors depend lesser on noises for future price discovery.

Conclusion

We hypothesise that, since an emerging market is viewed as a less efficient market, an examination of the behaviour of noise traders in such market is important. It is expected that being less efficient, the future price determination in such a market would be driven by a considerable extent on noise trading rather than on fundamental information. We document that an unknown factor playing a dominant role and the nascent noises are in fact to a very limited extent used by the investors to predict future prices in order to formulate decisions rules. The results show that intra-day volatility noise as given by the variable log of the spread high and low prices is most used, while the investors least use overnight volatility measure given by the spread between opening and previous closing prices. It demonstrates that the efficiency of the market is generally robust when compared to the developed market. The investigation of the behavior of the noise traders during falling and rising phases of the market does not reveal any remarkable difference of behavior. Such a phenomenon establishes that in an emerging market during economically opposite phases the efficiency of the market remains the same.

Table I
Regression Results
Period : November 1, 1999 To October 31, 2000 (Distressed Period)

The following multiple regression model is used :

$$Y = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{3i} + \varepsilon$$

Y = log of stock price (closing price)

x_{1i} = log (Spread of high minus low quotes of previous day),

x_{2i} = Spread of opening minus previous closing price of previous day,

x_{3i} = log (Turnover of previous day)

β_0, β_1, β_2, β_3 are regression coefficients and ε is the error term.

Firm's Name	β_o	t	P	β_1	t	p	β_2	t	p	β_3	t	p	R^2	AdjR^2
ABB	2.134	98.646	.000	.09141	3.824	.000	-.000187	-.232	.817	.085	5.224	.000	.343	.335
ACC	1.297	16.393	.000	.144	4.129	.000	.004701	2.095	.037	.213	7.253	.000	.552	.546
Bajaj Auto	2.486	177.518	.000	-.0501	-4.764	.000	-.000882	-1.004	.316	.049	6.848	.000	.162	.152
BHEL	2.253	32.166	.000	.334	9.730	.000	.004582	1.979	0.019	-.134	-4.753	.000	.287	.278
BPCL	2.242	55.145	.000	.274	10.910	.000	-.001084	1.010	.314	-.0814	-4.305	.000	.333	.325
Britannia	2.788	08.604	.000	-.00356	-.161	.872	-.000454	1.248	.213	.0211	1.321	.188	.016	.004
Cipla	2.646	42.801	.000	.229	8.968	.000	.001	3.861	.000	-.0186	-.799	.421	.306	.298
Colgate	2.000	92.886	.000	-.0551	-2.791	.000	.00051	.352	.725	.132	10.875	.000	.377	.369
Dabur	2.434	60.806	.000	.230	10.148	.000	-.00021	-.796	.427	.057	2.709	.001	.437	.430
Dr Reddy	3.054	70.813	.000	-.05482	2.928	.000	.00021	1.640	.102	-.012	-.729	.467	.046	.035
GAIL	1.847	75.254	.000	-.000532	-0.022	.982	.0059	2.087	.040	-.009	.-547	.586	.047	.015
Grasim	2.098	42.384	.000	.136	4.307	.000	.00166	1.956	.052	.086	3.404	.001	.271	.262
Guj Amb	2.113	23.456	.000	.355	9.908	.000	-.00041	-.919	.359	-.042	-1.043	.298	.329	.321
ITC	2.562	51.781	.000	-.0229	-1.164	.245	.000966	3.282	.001	.09	5.993	.000	.169	.159

HCL Tech	2.676	31.910	.000	.101	3.491	.001	.00061	4.875	.000	.0807	2.601	.000	.252	.240
HDFC	2.018	45.716	.000	.151	4.845	.000	.0028	1.994	.047	.068	2.847	.005	.276	.267
Hero	2.900	128.532	.000	.02474	1.702	.090	.00025	1.874	.062	.027	2.828	.005	.092	.080
HLL	3.101	24.920	.000	.803	38.678	.000	-.00009	-1.249	.213	-.405	.904	.000	.861	.860
HPCL	1.961	46.710	.000	.103	4.554	.000	.00409	2.276	.024	.037	1.962	.051	.188	.178
Indian Hotels	2.221	110.972	.000	.119	6.071	.000	-.00216	-2.747	.006	.039	2.968	.003	.284	.275
IPCL	1.299	29.204	.000	-.001869	.053	.958	-.007	-1.66	.098	.223	10.023	.000	.440	.433
Infosys	4.343	67.598	.000	-.07198	5.179	.000	.00002	2.433	.016	-.138	-9.972	.000	.336	.328
MTNL	2.404	34.566	.000	.411	16.297	.000	.0042	3.989	.000	-.151	-6.310	.000	.577	.572
M & M	2.202	31.083	.000	.289	11.256	.000	-.0044	-4.74	.000	-.038	-1.309	.192	.400	.393
ONGC	1.948	78.594	.000	.112	3.652	.000	-.00097	-.507	.613	.097	5.154	.000	.252	.242
Oriental Bank	1.422	137.470	.000	.004996	.321	.748	-.00055	-.149	.881	.106	12.686	.000	.592	.587
Ranbaxy	2.242	84.623	.000	-.101	-5.351	.000	-.000034	-.128	.848	.209	22.149	.000	.733	.730
Reliance	2.204	31.972	.000	-.0122	-.513	.608	-.00062	-.527	.599	.0069	3.5632	.000	.069	.058
Satyam	2.863	16.339	.000	.744	29.785	.000	-.00022	3.050	.003	-.241	-6.520	.000	.793	.791
SAIL	.633	15.012	.000	.114	4.466	.000	.015	.896	.371	.160	8.885	.000	.677	.673
SUN	1.930	25.169	.000	.524	14.895	.000	.00028	3.267	.001	.036	1.009	.314	.583	.578
Tata Chem	1.360	82.283	.000	-.0574	-3.340	.001	.0052	1.946	.053	.182	17.060	.000	.608	.604
TISCO	1.648	40.137	.000	-.0474	-2.024	.044	.0016	.729	.467	.145	9.059	.000	.357	.349
Tata Tea	2.088	38.536	.000	.309	10.154	.000	.0012	1.521	.129	.038	1.376	.170	.494	.488
VSNL	2.484	38.691	.000	.414	14.360	.000	.00025	1.521	.130	-.065	-2.938	.004	.475	.469
WIPRO	2.878	36.283	.000	.149	5.233	.000	.00025	3.374	.001	.0645	2.814	.005	.235	.225
Zee	2.427	10.034	.000	.693	20.979	.000	.00005	1.498	.135	-.160	-3.165	.002	.652	.648

Table I I
Regression Results
Period : November 1, 2004 To October 31, 2005 (Rising Period)

The following multiple regression model is used :

$$Y = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{3i} + \varepsilon$$

Y = log of stock price (closing price)

x_{1i} = log (Spread of high minus low quotes of previous day),

x_{2i} = Spread of opening minus previous closing price of previous day,

x_{3i} = log (Turnover of previous day)

β_0, β_1, β_2, β_3 are regression coefficients and ε is the error term.

Firm's Name	β_o	t	p	β_1	t	p	β_2	t	p	β_3	t	p	R^2	Adj. R^2
ABB	2.718	62.453	.000	.03331	1.274	.204	-.00054	-1.65	.100	.133	7.772	.000	.271	.262
ACC	2.630	65.012	.000	.165	9.301	.000	.00075	1.17	.243	-.0593	-4.646	.000	.261	.252
Bajaj Auto	2.642	62.455	.000	.120	5.727	.000	-.00041	1.519	.130	.0826	5.796	.000	.329	.321
BHEL	2.969	55.88	.000	.226	10.991	.000	.00101	2.823	.005	-.107	-5.592	.000	.329	.321
BPCL	2.443	126.703	.000	.00025	.022	.982	.00033	.731	.465	.0464	6.744	.000	.199	.189
Britannia	2.878	151.53	.000	.07454	5.964	.000	.0038	.163	.627	-.0043	-.487	.627	.142	.131
Cipla	2.467	66.694	.000	.08216	5.435	.000	-.00068	.978	.329	-.0204	-1.571	.117	.114	.103
Colgate	2.062	89.031	.000	.03697	1.781	.076	-.00087	-.650	.517	.0938	8.564	.000	.338	.330
Dabur	1.831	41.647	.000	.104	3.807	.000	-.0031	-1.36	.175	.0698	3.541	.000	.210	.201
Dr Reddy	2.819	130.792	.000	.0033	2.961	.003	-.000026	-.108	.914	.00735	.884	.378	.066	.055
GAIL	2.276	105.381	.000	.0373	3.764	.000	-.000073	-.084	.933	.00157	2.091	.038	.141	.130
Grasim	3.003	121.210	.000	.01675	1.408	.161	-.00022	-1.337	.183	.0188	2.199	.029	.051	.040
Guj Amb	2.692	16.89	.000	.878	26.319	.000	.00247	4.955	.000	-.312	-6.300	.000	.141	.741
ITC	3.622	25.236	.000	.766	24.840	.000		2.010	.045	-.451	.566	.000	.775	.773
HCL Tech	2.509	77.693	.000	.0809	5.486	.000	-.00052	-1.301	.195	-.0065	-.589	.556	.163	.153
HDFC	2.578	75.342	.000	.0597	4.386	.000	-.00017	-.702	.483	.0335	2.934	.004	.153	.143
Hero Hon	2.694	72.731	.000	.113	6.962	.000	.00086	2.095	.037	-.024	-1.809	.072	.175	.165
HLL	1.928	53.818	.000	.0458	3.210	.002	.0014	3.210	.002	.06356	5.465	.000	.280	.271
HPCL	2.310	114.444	.000	.003455	.324	.747	-.00018	-367	.714	.0614	8.633	.000	.307	.298

Indian Hotels	2.594	110.210	.000	.04463	2.505	.013	.0011	3.206	.002	.0596	6.872	.000	.289	.280
IPCL	2.007	92.402	.000	-.00498	-.416	.677	-.0004	-.256	.796	.0743	9.677	.000	.407	.400
Infosys	3.365	65.760	.000	.02896	2.270	.024	.000005	.048	.962	-.0178	-1.359	.175	.021	.009
MTNL	1.872	81.502	.000	-.041	-3.285	.001	.0112	.990	.323	.0859	10.091	.000	.330	.322
M & M	2.479	37.634	.000	.0929	3.899	.000	.000425	2.133	.034	.0327	1.595	.112	.104	.093
ONGC	2.903	75.039	.000	.0715	6.992	.000	-.00048	-2.600	.010	-.0113	-1.085	.278	.178	.168
Oriented Bank	2.250	94.073	.000	.0109	.765	.445	.0026	3.536	.000	.0583	6.408	.000	.277	.269
Ranboxy	3.346	33.192	.000	.429	9.338	.000	.00075	3.065	.002	-.274	-8.389	.000	.302	.294
Reliance	2.284	28.5	.000	.0333	1.485	.139	.00055	.914	.361	.100	4.874	.000	.188	.178
Satyam	2.422	30.890	.000	.0839	4.90	.000	.00043	.464	.643	.0336	1.600	.111	.131	.120
SAIL	1.594	39.49	.000	.0436	3.098	.002	-.0049	-1.442	.151	.0403	3.699	.000	.172	.161
SUN	2.635	89.977	.000	.0821	5.741	.000	.00085	2.558	.011	-.00167	-.135	.893	.154	.144
Tata Chem	2.021	93.976	.000	-.0003	-.020	.984	.00154	1.392	.165	.0698	7.815	.000	.299	.290
TISCO	2.263	34.567	.000	.0242	1.687	.093	-.00025	-.677	.499	.0673	3.966	.000	.124	.113
Tata Tea	2.477	49.799	.000	.197	7.924	.000	-.00166	-1.761	.079	.0204	1.078	.282	.265	.256
VSNL	1.947	140.595	.000	-.083	-4.842	.000	.00101	1.164	.246	.171	26.280	.000	.832	.830
WIPRO	2.812	25.859	.000	.197	5.968	.000	.00074	2.766	.006	-.0725	-2.104	.036	.139	.128
Zee	1.930	81.901	.000	-2.23	-1.574	.117	.0001	.104	.917	.0851	9.449	.000	.366	.358

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