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Bootstrap Estimate of a Behavioral Stock Price Model

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Abstract

A behavioral stock price model that incorporates inertia in investor behavior is developed and estimated. The estimates are consistent but biased, because of the presence of lagged dependent variables and errors-in-variables. The method of recursive bootstrap overcomes these problems and seems to provide a more accurate estimate of the behavioral model.

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1 Introduction

In this paper we develop a model for stock price behavior that takes into account time, information and cognitive resource constraints faced by investors. We argue that in an uncertain world investors use 'rules of thumb' in decision making. Popular stock investment strategies are often fads based on market generated data, especially share price as opposed to accounting data given in the company financial reports. Agents assume the current market valuation to be a reflection of the market's assessment of future prospects. Acting on the belief that prices will be what they were, investors use market valuation to pick stocks. Such behavior is self fulfilling and reflects inertia in investor behavior which then becomes the basis for market action.

This behavioral model is estimated using Ordinary Least Squares method and the model is tested for the presence of inertia. Though the regression coefficients of model are consistent, yet because of the presence of lagged dependent variables in the model the estimates are biased. We therefore evaluate the model using the technique of bootstrap.

The bootstrap is a resampling method used to derive the distribution of an estimator or a test statistic in cases where the sample size is too small for first order asymptotic theory to give a good approximation to the true distribution. The bootstrap is based on the idea that the sample is a good representation of the underlying population distribution. It amounts to treating the data as if they were the population for the purpose of evaluating the distribution of interest. Under mild regularity conditions, the bootstrap yields an approximation to the distribution of an estimator or the statistic that is at least as accurate as the approximation obtained from the first order asymptotic theory.

2 A Behavioral Model of Stock Prices

The behavioral approach to study of economics takes a realistic view of human problem solving capabilities and assumes them to be imperfectly rational (Mullainathan and Thaler 2000). It assumes that individuals aim for a 'satisfying behavior' rather than a 'maximizing behavior'. Further by allowing for the fact that individuals may not always choose what is best, this approach identifies the possibility of a market being in a perpetual state of disequilibrium. In the capital market, for instance, the market price will deviate from the equilibrium price depending upon the strength of the irrational traders vis-a-vis the rational traders in the market. While the trading by rational traders traces the path towards equilibrium, trading activities of irrational traders pushes the market away from the equilibrium point. The equilibrium prices are a weighted average of the beliefs of rational and irrational traders, and the influence of either group on prices depends upon their risk bearing capacity. Arbitrage will, therefore, not eliminate mispricing. Arbitraging does not work efficiently, since it is hard for an investor to know whether other investors have yet detected and acted upon it.

Persistent mispricing might also occur because some relevant piece of public information is either ignored or misused by everyone leading to market prices being regularly at odds with fundamental values. All individuals have biases especially under conditions when information is slack. While it might be argued that in the modern day computerized world, information is no longer a constraint, the question of quality of information, its proper interpretation and analyses still remains. And since individuals have similar biases, it will be incorrect to assume that errors cancel out in equilibrium and therefore that the estimated values will approximate the true values. Neoclassical economists arguing for the existence of equilibrium believed that individuals learn from past experiences and therefore would avoid making the same mistake. However, since there are some opportunity costs to learning it is possible that even a completely 'rational' learner will chose not to deviate from the existing position and remain in a non-optimal equilibrium if the cost of trying something else is too high. Moreover, the time required to converge to an equilibrium strategy can be extremely long, especially in a situation of changing environment. Thus, markets can be in a situation of perpetual non-convergence.

Faced with information, time and resource constraints and also a stock price series that exhibits random walk, investors find that the best forecast of the future price is in fact the current price. Individuals learn from economic experiences and form a general conclusion from knowledge of particular instances. Going by past experiences, individuals display inertia or habit persistence in their behavior. In a constantly changing world behavioral inertia plays the important role of imparting stability in individual's behavior. Inertia produces highly auto-correlated time series in which random events have lasting effects.

Individuals are however free to follow their own will. And if they are overconfident about their abilities they may deviate from the tried and tested path. Individuals are often overtaken by whims and fancies which creates uncertainity in all economic behavior. Social and economic advances come from 'irrational' behavior of such agents. Such impulsive action (caprice) on the part of individuals provides a mechanism of behavioral variation, which promotes society's advance. Caprice also exhibits inertia or pattern in variation. Variations that were successful in the most recent past will tend to remain successful in the near future as well, implying positive autocorrelations among the innovations. By explicitly identifying inertia and caprice, the Behavioral Inertia Model proposes a dynamic theory of economic phenomena.

The behavioral inertia model that we developed allows for biases in individual behavior and treats them as incompletely rational. The model is developed at the stock level rather than at the portfolio level. This is owing to the fact that investors rarely hold a well diversified portfolio (Barber and Odean 2000; Polkovinchenko 2003; Goetzmann and Kumar 2004). Investors' personal characteristics, their stock preferences and their behavioral biases jointly influence their diversification choices (Goetzmann and Kumar 2004, Kumar & Lim 2004). Huberman (2001) also reported the tendency of household investments to be primarily concentrated in their employer's stocks and in general in stocks of companies registered in their country as against foreign company stocks. These phenomena provide compelling evidence that people invest in the familiar stocks, while often ignoring the principles of portfolio theory.

Further, by working directly with prices rather than stock returns one can draw unambiguous conclusions. With returns, a choice between equal weighted versus value weighted returns has different implications for the behavior of the stock markets. More importantly, by working with prices rather than returns, we avoid the crucial question of unit of time for returns. Measurement choice between average monthly abnormal returns vis-a-vis buy and hold abnormal returns has severe effect on the outcome of the study. Choice of a normal period to estimate a stock's expected return is also problematic as stocks can show return continuation in the short run and mean reversion in the long-run.

2.1 The Model

We capture the inertia in stock prices and the market dynamism by formulating an asset pricing model as a function of lagged prices and C_t the caprice element.
Assuming inertial decay

$\mathrm{P}_t = \alpha_0 \, P_{t-1}^{\alpha_1} \, C_t$ (1)

If caprice also experiences the same type of exponential decay then

$\mathrm{C}_t = X_t^{\beta} \, C_{t-1}^{\rho} \, \epsilon_t$ (2)

where X_t is 1 x k vector of explanatory variables, β is a k x 1 vector of regression coefficients. ρ is the auto-regression coefficient for caprice, a measure of its persistence and ϵ_t is the truly random irreducibly stochastic past. Re-writing the above equations in logarithmic form, we get

$\ln P_t = \ln \alpha_0 + \alpha_1 \ln P_{t-1} + \ln C_t$ (3)

$\ln C_t = \beta \ln X_t + \rho \ln C_{t-1} + \ln \varepsilon_t$ (4)

and further

$\ln C_{t-1} = \ln P_{t-1} - \ln \alpha_0 - \alpha_1 \ln P_{t-2}$ (5)

Thus, for each stock i,

$$\begin{aligned}
\ln P_{it} &= \ln \alpha_{0i} + \alpha_{1i} \ln P_{it-1} + \beta_i \ln X_{it} + \rho_i \left[\ln P_{it-1} - \ln \alpha_{0i} - \alpha_{i1} \ln P_{it-2}\right] + \ln \varepsilon_{it} \\
&\text{or} \\
\ln P_{it} &= \ln \alpha_{0i} + (\alpha_{1i} + \rho_i) \ln P_{it-1} + \beta_i \ln X_{it} - \rho_i \ln \alpha_{0i} - \rho_i \, \alpha_{1i} \ln P_{it-2} + \ln \varepsilon_{it} \\
&\text{or} \\
\ln P_{it} &= (1-\rho_i) \ln \alpha_{0i} + (\alpha_{1i} + \rho_i) \ln P_{it-1} - \rho_i \, \alpha_{1i} \ln P_{it-2} \\
&+ \beta_{1i} \ln X_{1it} + \beta_{2i} \ln X_{2it} + \beta_{3i} \ln X_{3it} + \beta_{4i} \ln X_{4it} + \ln \varepsilon_{it} \qquad (6)
\end{aligned}$$

(obtained by decomposing X_{it} into its components) Thus, the testing of the model involves running the following regression

$$\begin{aligned}
\ln P_{it} &= (1-\rho_i) \ln \alpha_{0i} + (\alpha_{1i} + \rho_i) \ln P_{it-1} - \rho_i \, \alpha_{1i} \ln P_{it-2} + \beta_{1i} \ln X_{1it} \\
&+ \beta_{2i} \ln X_{2it} + \beta_{3i} \ln X_{3it} + \beta_{4i} \ln X_{4it} + \nu_t \qquad (7)
\end{aligned}$$

$$\text{where } \nu_t = \ln \varepsilon_{it}$$

The presence of inertia is ascertained by testing for the

$H_0 : (\alpha_{1i} + \rho_i) - \rho_i \, \alpha_{1i} = 1$

i.e. sum of AR(autoregressive) coefficients = 1

2.2 Data and Empirical Testing of the Model

The late 1990s and the early part of 2000 was marked by the dominance of Technology, Media and Telecom (TMT) stocks in stock markets world wide. The Behavioral Inertia Model was tested using data from the Indian stock markets and the study period covered was from April 1999 to November 2004. From the TMT stocks underlying the various Bombay Stock Exchange (BSE) and National Stock Exchange (NSE) indices only 35 companies were found to have a continuous price data and information on economic fundamentals of the company for the period covered under the study. These, therefore, formed the sample for the present study. Monthly price data on the selected companies was obtained from the website of BSE. Various websites including those of BSE (www.bseindia.com), NSE (www.nseindia.com), India Infoline (www.indiainfoline.com) and Sify (www.sify.com) provided detailed information on the sample companies. Data on par value, number of shares issued, dividend rate, and book-value were thus collected from these sources. Market equity was estimated as a product of the number of shares outstanding and price in the March of year T. The BE/ME ratio for year T was obtained by dividing the book value of the firm for the fiscal year ending in calendar year T-1 by the market equity at the end of December T-1. The stock level β for the year T+1 was estimated by regressing excess return on stock on the excess market return i.e. the following time-series regression was run using monthly data (t) for year T

$r_{it} = \alpha_i + \beta_i r_{mt} + \varepsilon_{it}, \forall i$
where
$r_{it} = R_{it} - R_{ft}$ and
$r_{mt} = R_{mt} - R_{ft}$
Here $R_{it} = \frac{P_{it} - P_{i(t-1)} + D_{it}}{P_{i(t-1)}}$

P_{it}, $P_{i(t-1)}$ are stock prices in time period t and t-1 and D_{it} is the dividend in time period t of stock i. And R_{ft} is the rate of interest on savings account which was used as a proxy for risk free rate of return.

The BSE 500 Index(I_t) was taken as a proxy for market portfolio and the value on this index was again collected from BSE website. Return on BSE Index was then calculated as

$R_{mt} = \frac{I_t - I_{t-1}}{I_{t-1}}$

In our exercise the explanatory variables included are natural log of book-to-market value (lnB/M), natural log of market value (lnMV) and natural log of beta (lnbeta). Of the 35 stocks 3 stocks namely ASM Tech, BPL and Nelco had negative BE/ME value and were therefore dropped. Many of the stocks reported negative beta values for part of the time period under consideration. Moreover, the coefficient of beta was found to be insignificant in an earlier exercise of univariate regression of excess returns on stocks over the estimated betas. However, considering the fact that for long, beta dominated the risk-return models, we saw it reasonable to continue including beta in the set of explanatory variables. To take care of the problem of finding natural log for negative betas we bifurcated the beta variable into ln β positive and ln β negative. For positive beta values natural log was estimated and was recorded as variable lnbeta positive. For such periods with positive beta, the variable lnbeta negative shows the value of zero. Similarly, for negative betas, the ln value of $|\beta|$ was estimated (i.e. excluding negative sign) and this was treated as variable ln β negative. Here the variable ln β positive has elements zero for the corresponding time period. Out of the thirty-two sample companies thirteen had two beta variables of lnbeta and lnbeta negative.

Any meaningful exercise using time series data is possible only after verifying the stationarity of the series under consideration. Towards this end ADF test was conducted on the price series, natural log of the book to market value (lnBM), natural log of the market value (lnMV), natural log of beta(ln β) and natural log of beta negative(ln β neg). The results of ADF test on all the variables used in the model (given in Appendix 1) show that only for the ln price series the null of Unit root with trend and intercept is not accepted at 5% (though not rejected at 1%) for a small number of companies. The p values of the likelihood ratio test of the coefficient on the one time lag of the dependent variable and the trend being jointly equal to zero shows that for Afte, Crest, DSQ, Eserve, Hinduja, InfoSys, Moser, MTNL, Orient, Penasoft, TataElxsi and Vindhyas the absence of trend is accepted at 1% but not at the 5% level of significance. Similarly, the presence of Unit root with intercept alone is not accepted by lnprice series of Eserve, Hinduja and Moser at 5% level of significance. For all other series the null hypothesis of Unit root is accepted with trend alone at 5% level of significance.

After ascertaining the independence of the error terms (see Appendix 2) we estimated the model by running the following regression on price series of nineteen companies which had positive beta values throughout the study period.

$$\ln P_t = \beta_0 + \beta_1 \ln P_{t-1} + \beta_2 \ln P_{t-2} + \beta_3 \ln BM + \beta_4 \ln MV + \beta_5 \ln \text{beta}$$

For the thirteen companies which had negative betas for part of the sample period the beta dummy of lnbeta negative was included in the above regression. Thus, the following regression was run.

$$\ln P_t = \beta_0 + \beta_1 \ln P_{t-1} + \beta_2 \ln P_{t-2} + \beta_3 \ln BM + \beta_4 \ln MV + \beta_5 \ln \text{beta} + \beta_6 \ln \text{betaneg}$$

The results of the above regression are reported in Table 1. The last column of the Table gives us the ‘t’ values calculated for the null hypothesis of

$$\beta_1 + \beta_2 = 1$$

From the Table 1 we see that the one time lagged price for all the series is strongly significant and has a positive feedback effect on the current price level. But the series lagged by two time periods has a low slope coefficient and is also highly insignificant. Moreover, whether P_{t-2} pushes the current price in the same direction or in the opposite direction is not clear from the mixed results obtained. Again lnBM and lnMV are individually significant only for seven companies, whereas the two beta variables, lnbeta and lnbeta negative are significantly different from zero only for five companies. But taken together, the two economic fundamental variables along with the beta dummies and the two lagged price variables do a very good job in modeling the price behavior. This can be seen from the R^2 statistic reported. In all the 32 cases the ‘F’ test of all the coefficients being equal to zero is rejected.

From the t statistic reported in the last column of Table 1 it is clear that the null of inertia evaluated at 1% level is not accepted in the following series- Bluestar, Finiolex, Jain, Mphasis, MTNL, NIIT, Satyam, TataElxsi, Wipro and Zensar. In the behavioral inertia approach the only distributional assumption made about the error terms is that they are identically and independently distributed.Therefore, we also evaluated the model using the Wald test, an asymptotic test which does not require the assumption that the error term is normally distributed.

The results of Wald test reported in Table 2 also confirms the presence of inertia in twenty two of the thirty two sample companies. In fact the null hypothesis was rejected for the same set of companies which failed the t test.

Though the regression coefficients of our model are consistently estimated by OLS (as errors are serially uncorrelated) their small sample properties are not good. In particular, the OLS estimates are biased. This arises because of the presence of lag-dependent variables in the model which violates the fixed explanatory variable assumption. With time series data the independence of the error term from the explanatory variables must be true not only in each time period(contemporaneously uncorrelated) but also between time periods(independence). Even when there is no contemporaneous correlation i.e. $\ln P_{t-1}$ and $\ln P_{t-2}$ are independent of ϵ_t (because of no serial correlation) there will still be a dependency of $\ln P_{t-1}$ on ϵ_{t-1} and $\ln P_{t-2}$ on ϵ_{t-2}.

Moreover, lnbeta and lnbetaneg used in the model are estimated variables and hence lead to errors in the variables problem. This causes biases not only in the coefficients of these variables but also in the coefficients of $\ln P_{t-1}$ and $\ln P_{t-2}$. The direction of the bias can be ascertained only after looking at the value of the coefficients of lnbeta, lnbeta negative, and the covariance between the explanatory variables. It will thus vary from equation to equation. Thus, a priori, the direction of the bias cannot be inferred.

Further when both the null and the alternative models involve lagged dependent variables the ‘F’ statistic does not follow the ‘F’ distribution in finite samples. Again, the Wald test is an asymptotic test and suffers from size distortion in finite samples.

Thus the OLS estimates, though consistent and hence satisfy our requirement for the test of hypothesis, can be improved upon. The technique of bootstrap through random resampling of residuals generates the model in such a way as to take care of the above mentioned problems. The approach of recursive bootstrap estimation, which breaks the correlation between regressors and residuals of the model, thus forms our next exercise.

3 The Technique of Bootstrap

The bootstrap, a technique introduced by Efron (1979) is a resampling method used to derive the distribution of an estimator or a test statistic in cases where asymptotic distribution is difficult to calculate. The bootstrap is based on the idea that the sample is a good representation of the underlying population distribution. The appeal of the bootstrap in finite samples is in fact two-fold. Not only is the bootstrap more accurate, but it also does not entail the algebraic complexity of higher order approximations (Horowitz 1995). The estimators derived from the asymptotic theory though consistent (and often super-consistent) have substantial small sample biases. Further, first order asymptotic theory often gives a poor approximation to the distribution of test statistics with the sample sizes available in application. As a result, the nominal levels of tests based on asymptotic critical values can be very different from the true levels. The bootstrap on the other hand, provides improved finite sample critical values for the test statistics and confidence intervals with improved finite sample coverage probabilities.

Statistical inference in a classical framework involves either estimating p values (where the p value is defined as the probability of drawing the sample from the population being tested given the assumption that the null hypothesis is true) or constructing confidence intervals. Simulation based hypothesis testing is generally easier and more reliable than constructing simulation based confidence intervals. A key objective in the classical testing of statistical hypothesis is achieving good power while controlling the size of the tests. The first order asymptotic approximation can be very inaccurate when one is dealing with small samples. One reason is that for asymptotic theory to be valid it is necessary that the p value function does not depend on the data generating process, which is not usually the case in small samples. As a result the true and nominal probabilities that a test rejects a correct null hypothesis can be different when the p value is obtained from asymptotic distribution of the test statistic. Since the bootstrap distribution is able to mimic possible skewness of the finite sample distribution, it may account for deviations of the actual distributions from asymptotic distribution. Therefore, it can be used to approximate the finite sample distribution of various large sample tests like Wald, LR etc. (Canepa and O'Brien 2000).

The bootstrap method does not require any distributional assumptions and bootstrap errors are generated non-parametrically by resampling the estimated residuals. The essential requirement for using bootstrap tests is that the underlying test statistic should be asymptotically pivotal, i.e. as the sample size tends to infinity, any dependence of the distribution on unknown parameters or other unknown features of the data generating process must vanish. Most of the statistic used in econometric practice are asymptotically pivotal. Under the null hypothesis these statistics have asymptotic distributions like standard normal or chi-squared that does not depend on the unknown parameters. The bootstrap provides higher order asymptotic approximation to the distribution and critical values of "smooth" asymptotically pivotal statistic.

The bootstrap may also be applied to the statistics that are not asymptotically pivotal, such as regression coefficients, but it does not provide a higher order approximation to their distributions. Bootstrap estimates of the distribution of statistics that are not asymptotically pivotal have the same accuracy as the first order asymptotic approximations.

3.1 Bootstrap Estimation of the Model

In the OLS exercise for estimating the behavioral inertia model we undertook two large sample test- the LM test for detecting serial correlation and the Wald test for the test of inertia. In small samples these asymptotic tests may have size distortions and therefore actual levels of significance have to be established for a correct test of the null hypothesis. Many Monte-Carlo studies have found that the use of asymptotic χ^2 distribution leads to misleading inferences. The bootstrap method can be used to get more accurate small sample inferences (Horswell and Looney 1992; Deschamps 1996; Mecklin and Mundfrom 2005).

The bootstrap approach for testing a hypothesis involves estimating the model under the constraints given by the null hypothesis. Thus, for example for the test of hypothesis $\beta = \beta_0$, the model under consideration (say $Y_t = \beta\, X_t + u_t$) is estimated by putting $\beta = \beta_0$, and the residuals $\widetilde{u}_t = Y_t - \beta_0\, X_t$ are generated. This $\widetilde{u}_t$ vector of residuals forms the bootstrap DGP from which resampled vectors are drawn with replacement. The reason for estimating the model under the null is that if the null of $\beta = \beta_0$ is true, but the OLS estimator $\hat{\beta}$ gives a value of β far away from β_0, the empirical distribution of the residuals will suffer from a poor approximation of the distribution of errors under the null.

The bootstrap samples of residuals are next plugged back in the model and Y*(bootstrap samples of Y) are generated using β_0 (i.e. null hypothesis parameter values). Thus, $Y_t^* = \beta_0\, X_t + u_t^*$.

In the next step, the generated Y* is again regressed on the given set of explanatory variables, a new set of parameters estimated and the model is tested for null hypothesis.

When the error terms in the model are serially correlated or the model includes lagged dependent variables, bootstrap sampling should be done in such a way that the bootstrap error terms display the same sort of time dependency as the real ones. Considering the fact that one doesn't know how the real terms were generated, special bootstrap methods have to be used to take care of this problem.

With lagged dependent variable in the R.H.S of the model, bootstrap sample of errors have to be generated sequentially by replacing the lagged dependent variable of the model by the generated values of the dependent variable of the earlier period.

3.2 Bootstrapping the Breusch-Godfrey serial correlation test

Mantalos (2003) had pointed out that when the autocorrelation of price change is small but persistently positive (or negative) standard test for significance of autocorrelation are unlikely to reject null of serial correlation. Despite the presence of lagged dependent variables the Breusch-Godfrey test (see Appendix 2) does not support the presence of serial correlation in any of the sample companies. To verify the absence of serial correlation we redid the Breusch-Godfrey test using the technique of bootstrap.

The Breusch-Godfrey test is a general test for serial correlation valid for both autoregressive and moving average errors. This test is derived from the Lagrange multiplier (LM) principle.

Consider the regression model

$$Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \beta_1 X_{1t} + \beta_2 X_{2t} + ... \beta_k X_{kt} + u_t, \forall (t = 1, \ldots, T) \tag{8}$$

and

$$u_t = \rho_1 u_{t-1} + \rho_2 u_{t-2} + ... \rho_q u_{t-q} + e_t \tag{9}$$

$$e_t \sim IN(0, \sigma^2)$$

The null hypothesis to be tested is

$$H_0 : \rho_1 = \rho_2 = \ldots = \rho_q = 0$$

The Breusch-Godfrey test involves estimating equation 8 by OLS and obtaining the least squares residuals $\hat{u}_t$. Next the following regression equation is estimated

$$\hat{u}_t = \gamma_0 + \gamma_1 Y_{t-1} + \gamma_2 Y_{t-2} + \delta_1 X_{t-1} + ... + \delta_k X_{t-k} + \sum_{i=1}^{q} \hat{u}_{t-i} \rho_i + \eta_t \tag{10}$$

and a test of the coefficient of all the $\hat{u}_{t-i}$ being equal to zero is undertaken. Since in the bootstrap approach the confidence intervals are not based on asymptotic theory but are sample determined the significance or otherwise of each parameter can be judged only after estimating the confidence interval of each parameter. However, as there are many alternative ways to compute bootstrap confidence intervals and since they may yield quite different results, we have chosen to test the hypothesis by calculating the p value of the test. The p value of the test is the proportion of samples for which the bootstrap statistic exceeds the actual sample statistic. Here the bootstrap statistic of interest is a χ^2 variable with d.f. q which is obtained from the calculated F and the number of restrictions q.
An alternative estimation procedure involves estimating the OLS coefficients for equation 8 and getting the residuals and again estimate the following model by OLS:

$$Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \beta_1 X_{t-1} + ... + \beta_k X_{t-k} + \sum_{i=1}^{q} \hat{u}_{t-i} \rho_i + \eta_t \tag{11}$$

The F statistic for testing the null hypothesis is again computed as q F $\sim\chi^2$ with q degrees of freedom and inference is drawn.

For bootstrapping the test for serial correlation we use the recursive bootstrap approach. Since our model involves lagged dependent variables we generated bootstrap sample of Y* in a recursive manner so as to preserve the time dependency of the Y series. This approach involves the following steps:

1. Estimate the model under the null of no serial correlation by regressing $\ln P_t$ on $\ln P_{t-1}$, $\ln P_{t-2}$, $\ln B/M$, $\ln MV$, lnbeta and lnbeta negative.

2. Obtain the OLS residuals u_t. From this residual vector through random resampling with replacement we generate a bootstrap sample vector of residuals.

3. Using the first element of the resampled residual vector along with the OLS coefficients of $\ln P_{t-1}$, $\ln P_{t-2}$, $\ln B/M$, $\ln MV$, lnbeta and lnbeta negative obtained in step 1, and the first row of the following matrix of explanatory variables we generate $\ln P_1{}^*$.

$$\begin{bmatrix} 1 & \ln P_0 & \ln P_{-1} & \ln B/M_1 & \ln MV_1 & \ln \text{beta}_1 & \ln \text{betaneg}_1 \\ 1 & \ln P_1 & \ln P_0 & \ln B/M_2 & \ln MV_2 & \ln \text{beta}_2 & \ln \text{betaneg}_2 \\ 1 & \ln P_2 & \ln P_1 & \ln B/M_3 & \ln MV_3 & \ln \text{beta}_3 & \ln \text{betaneg}_3 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & \ln P_{64} & \ln P_{63} & \ln B/M_{65} & \ln MV_1 & \ln \text{beta}_{65} & \ln \text{betaneg}_{65} \\ 1 & \ln P_{65} & \ln P_{64} & \ln B/M_{66} & \ln MV_{66} & \ln \text{beta}_{66} & \ln \text{betaneg}_{66} \end{bmatrix} \quad (12)$$

Thus,

$$\begin{aligned} \ln P_1^* &= \overset{\wedge}{\beta}_0 + \overset{\wedge}{\beta}_1 \ln P_0 + \overset{\wedge}{\beta}_2 \ln P_{-1} + \overset{\wedge}{\beta}_3 \ln \frac{B}{M}{}_1 + \overset{\wedge}{\beta}_4 \ln MV_1 \\ &\quad + \overset{\wedge}{\beta}_5 \ln \text{beta}_1 + \overset{\wedge}{\beta}_6 \ln \text{betaneg}_1 + u1_1^* \end{aligned} \quad (13)$$

where $\overset{\wedge}{\beta}_0$, $\overset{\wedge}{\beta}_1$, $\overset{\wedge}{\beta}_2$, $\overset{\wedge}{\beta}_3$ $\overset{\wedge}{\beta}_4$, $\overset{\wedge}{\beta}_5$, $\overset{\wedge}{\beta}_6$ are the OLS estimates and $u1_1^*$ the first element of the bootstrap resample residual vector.

4. For generating the second element of $\ln P_t{}^*$ we use the second element of the bootstrap sample residual vector along with the second row of the matrix of explanatory variables and OLS estimates but with $\ln P_1^*$ replacing $\ln P_1$.

5. The third and subsequent elements of $\ln P_t{}^*$ are generated similarly but with $\ln P_{t-1}^*$ and $\ln P_{t-2}^*$ replacing $\ln P_{t-1}$ and $\ln P_{t-2}$.

   The new vector of $\ln P_t^*$ is therefore given as

$$\begin{bmatrix} \ln P_1^* \\ \ln P_2^* \\ \ln P_3^* \\ \vdots \\ \ln P_{65}^* \\ \ln P_{66}^* \end{bmatrix} = \begin{bmatrix} 1 & \ln \mathrm{P}_0 & \ln \mathrm{P}_{-1} & \ln B/M_1 & \ln MV_1 & \ln \mathrm{beta}_1 & \ln \mathrm{betaneg}_1 \\ 1 & \ln \mathrm{P}_1^* & \ln \mathrm{P}_0 & \ln B/M_2 & \ln MV_2 & \ln \mathrm{beta}_2 & \ln \mathrm{betaneg}_2 \\ 1 & \ln \mathrm{P}_2^* & \ln \mathrm{P}_1^* & \ln B/M_3 & \ln MV_3 & \ln \mathrm{beta}_3 & \ln \mathrm{betaneg}_3 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & \ln \mathrm{P}_{64}^* & \ln \mathrm{P}_{63}^* & \ln B/M_{65} & \ln MV_1 & \ln \mathrm{beta}_{65} & \ln \mathrm{betaneg}_{65} \\ 1 & \ln \mathrm{P}_{65}^* & \ln \mathrm{P}_{64}^* & \ln B/M_{66} & \ln MV_{66} & \ln \mathrm{beta}_{66} & \ln \mathrm{betaneg}_{66} \end{bmatrix} \cdot \begin{bmatrix} \hat\beta_0 \\ \hat\beta_1 \\ \hat\beta_2 \\ \hat\beta_3 \\ \hat\beta_4 \\ \hat\beta_5 \\ \hat\beta_6 \end{bmatrix}$$

$$+ \begin{bmatrix} u1_1^* \\ u1_2^* \\ u1_3^* \\ \vdots \\ u1_{65}^* \\ u1_{66}^* \end{bmatrix} \tag{14}$$

6. In the next step the newly generated $\ln P_t{}^*$ vector is regressed on the matrix of explanatory variables given in equation (12) but with $\ln P_1$ and the subsequent $\ln P_t$'s being replaced by the generated values and the lagged residuals. Thus the new vector of coefficients is estimated using the following matrix of explanatory variables.

$$\begin{bmatrix} 1 & \ln P_0 & \ln P_{-1} & \ln B/M_1 & \ln MV_1 & \ln \mathrm{beta}_1 & \ln \mathrm{betaneg}_1 & u1_0^* & u1_{-1}^* \\ 1 & \ln P_1^* & \ln P_0 & \ln B/M_2 & \ln MV_2 & \ln \mathrm{beta}_2 & \ln \mathrm{betaneg}_2 & u1_1^* & u1_0^* \\ 1 & \ln P_2^* & \ln P_1^* & \ln B/M_3 & \ln MV_3 & \ln \mathrm{beta}_3 & \ln \mathrm{betaneg}_3 & u1_2^* & u1_1^* \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & \ln P_{64}^* & \ln P_{63}^* & \ln B/M_{65} & \ln MV_1 & \ln \mathrm{beta}_{65} & \ln \mathrm{betaneg}_{65} & u1_{64}^* & u1_{63}^* \\ 1 & \ln P_{65}^* & \ln P_{64}^* & \ln B/M_{66} & \ln MV_{66} & \ln \mathrm{beta}_{66} & \ln \mathrm{betaneg}_{66} & u1_{65}^* & u1_{64}^* \end{bmatrix} \tag{15}$$

7. The test of no serial correlation is done by running the F test and generating a χ^2 statistic as equal to 2xF (here 2 is the number of restrictions)

8. We repeat steps 2-7 one thousand times to generate one thousand resampled residual vector and corresponding one thousand $\ln P_t{}^*$ vectors, one thousand coefficient vectors and thousand χ^2 statistics.

9. Finally, the bootstrap point estimator and the bootstrap variance are calculated as $\hat\beta_{B.S} = \frac{\sum_{j=1}^{B} \beta_j^*}{B}, \hat V_{B.S} = \frac{\sum_{j=1}^{B} (\beta_j^* - \hat\beta_{B.S})^2}{B-1}$

where β_j^* is the estimated coefficient of the model and B is the number of bootstrap(see Table 3).

10. The p value of the Breusch-Godfrey test is obtained by finding the proportion of samples whose χ^2 statistic exceeds the χ^2 value of the original sample.
    The p values associated with the bootstrapping of Breusch-Godfrey test is given in Table 4.

The bootstrap results again strongly support the absence of serial correlation in residuals. Only three companies namely TataElxsi, Wipro and Zensar fail to accept the absence of serial correlation at 5 % level of significance. All the sample companies, however, accept the null at 1 % level of significance.

3.3 Bootstrapping the Wald test

A similar exercise was done for bootstrapping the Wald test, the steps for which are noted below:

1 The first step in the bootstrap exercise is to estimate the model under the null. Writing the set of restrictions $\beta_1+\beta_2 = 1$ in the form $Rb = r$ we get

$$R = \begin{bmatrix} 0 & 1 & 1 & 0 & 0 & 0 & 0 \end{bmatrix},$$
$$b^T = \begin{bmatrix} \beta_0 & \beta_1 & \beta_2 & \beta_3 & \beta_4 & \beta_5 & \beta_6 \end{bmatrix},$$
$$and$$
$$r = 1$$

A solution to the behavioral model under the null hypothesis restriction is possible as the number of rows of R is smaller than the number of columns of the R. Thus regressing $\ln P_t$ on $\ln P_{t-1}$, $\ln P_{t-2}$, $\ln B/M$, $\ln MV$, lnbeta and lnbeta negative under the null hypothesis restriction we get restricted least square estimates. The vector of RLS coefficient estimates can also be obtained by using the relation

$b_{RLS} = b_{OLS} + (X'X)^{-1}R'[R(X'X)^{-1}R']^{-1}(r - Rb)$.

Here X denotes the matrix of explanatory variables as given in equation (12).

2 Using the $\hat{b}_{RLS}$ coefficients and the $\ln P_t$ vector we next find $\hat{u}_{RLS}$,i.e. residuals of the restricted least square.

3 Now through random resampling with replacement we pick a vector containing sixty six elements from the restricted residuals set.

4 Using the first element of the bootstrap sample of residual and the first row of the matrix of explanatory variables given in equation (12) and $\hat{b}_{RLS}$ coefficients we estimate $\ln {P^*}_1$.

5 We next pick the element in the second row from the sampled vector of residuals and using the second row of the matrix of explanatory variables but with $\ln P^*{}_1$ replacing $\ln P_1$ and the $\hat{b}_{RLS}$ coefficient vector we generate $\ln P^*{}_2$.

6 For $\ln P_3^*$ we pick the third element in the $\hat{u}_{RLS}$ and using the third row of matrix of explanatory variables with $\ln P^*{}_1$ and $\ln P^*{}_2$ substituted for $\ln P_1$ and $\ln P_2$ and the $\hat{b}_{RLS}$ vector we estimate $\ln P^*{}_3$.

7 Subsequent elements of $\ln P^*{}_t$ are generated in a similar fashion by using $\ln P^*{}_{t-1}$ and $\ln P^*{}_{t-2}$

8 Now, using the generated vector of $\ln P^*{}_t$ and the new matrix of explanatory variables, i.e, the regressor and the regressand given in equation 14 we re-estimate the model by OLS.

9 The Wald test for the sum of the regression coefficients of the two lagged price variables adding up to one is undertaken for this new model and the χ^2 value noted.

10 Steps 3 to 9 is repeated thousand times to generate thousand vectors of bootstrap sample of residuals, thousand vectors of generated $\ln P^*{}_t$, thousand coefficient vectors and thousand χ^2 statistic.

11 The bootstrap estimates of each coefficient are then obtained as the mean and standard deviation of the respective estimated coefficients (see Table 5).

12 Finally the p value of the Wald test is obtained by finding the proportion of bootstrap samples whose χ^2 statistic exceeds the χ^2 value of the original sample.

The results of the above exercise are given in Table 6.

From Table 6 it is clear that the model now rejects the null for only two out of the thirty-two sample companies, evaluated at 1% level of significance. These two companies are namely Mphasis and NIIT. Evaluated at 5% the null is not accepted for a total of eight companies. These include Infosys, Mphasis and NIIT, Pentasoft, Satyam, VSNL, Zee, and Zenith.

4 CONCLUSIONS

The OLS exercise gave us consistent estimates, but had poor small sample properties. The estimates are biased because of the inclusions of lagged-dependent variables and the presence of error in the measurement of beta variable. Specifically, the coefficients for the lagged dependent variable are upwardly biased. The presence of error in the measurement of the variables lnbeta and lnbeta negative causes biases in not only the coefficients of these variables but also in the coefficients of $\ln P_{t-1}$ and $\ln P_{t-2}$. The direction of the bias can be ascertained only after looking at the value of the coefficients of lnbeta, lnbeta negative, and the covariance between the explanatory variables. Thus, a priori, the direction of the bias cannot be inferred and hence the reliability of the test statistics cannot be established. Further, the Wald test is an asymptotic test and suffers from size distortion in finite samples.

In order to overcome the above limitation, we employed the bootstrap test to evaluate our model. Bootstrapping asymptotically pivotal statistics such as LM and Wald statistics yields asymptotic improvements compared to the standard least squares formulas. Asymptotic χ^2 distributed tests are quite heavily affected by the sample size. By bootstrapping we replicate any skewness in the finite sample distribution and hence the bootstrap distribution of the statistic can account for deviations of the actual distribution from the asymptotic distribution. Bootstrap thus enables us to approximate the finite sample distribution of LM and Wald statistic and therefore more reliable inferences can be drawn.

The Breusch- Godfrey serial correlation test that we undertook in the OLS framework fails to detect any serial correlation. A bootstrap approach to this test also gave us the same result. Using the technique of recursive bootstrap, we estimated regression of $\ln P_t$ on all the explanatory variables and the lag of residuals. A χ^2 test of the coefficients of the two lag residual terms being equal to zero was undertaken. The result of such a test showed that except for three companies, namely, TataElxsi, Wipro and Zensar, the null hypothesis of no serial correlation was not rejected in any of the other companies at 5% level of significance. At 1% the absence of serial correlation was accepted for all the companies.

We next undertook the bootstrap test of behavioral inertia model. Because of the presence of lagged dependent variables we again used the technique of recursive bootstrap and estimated the distribution of the Wald test statistic. The p value associated with the test is obtained as the number of bootstrap samples in which Wald statistic is greater than the statistic obtained in the original sample. The results of the bootstrap test showed that for only two companies the p values were low enough to reject the null hypothesis of presence of inertia, evaluated at 1% level of significance. The rejection of the null hypothesis of presence of inertia in a smaller number of companies with the bootstrap approach as compared to the number rejected in the OLS framework leads us to strongly support our hypothesis of presence of inertia in the stock market during the study period. Thus, the study indicates bootstrap as a useful technique for drawing inferences in models with lagged dependent variables and estimated variables.

Table 1. Regression of $\ln P_t$ on $\ln P_{t-1}$, $\ln P_{t-2}$, $\ln BM$, $\ln MV$, $\ln beta$ and $\ln betanegative$

		C	$\ln P_{t-1}$	$\ln P_{t-2}$	$\ln BM$	$\ln MV$	$\ln \beta$	$\ln \beta$ Negative
Coefficient	ACE	1.8420	0.8945	-0.0383	-0.1636	-0.1028	0.1121	0.0000
Std. Error		1.2940	0.1297	0.1416	0.0905	0.0810	0.0947	0.0000
t-Statistic		1.4230	6.8988	-0.2708	-1.8073	-1.2702	1.1836	0.0000
Prob.		0.1600	0.0000	0.7875	0.0757	0.2089	0.2412	0.0000
		R-sq = 0.897341 **AdjR-sq** = 0.888786 **DW** = 2.032666 **Prob(F)** = 0 **t** = -1.663						
Coefficient	AFTE	3.0324	0.8964	-0.0345	-0.1410	-0.1182	0.2196	0.0000
Std. Error		4.1628	0.1312	0.1433	0.0823	0.1713	0.5980	0.0000
t-Statistic		0.7284	6.8352	-0.2407	-1.7135	-0.6900	0.3672	0.0000
Prob.		0.4692	0.0000	0.8106	0.0918	0.4928	0.7147	0.0000
		R-sq = 0.849264 **AdjR-sq** = 0.836702 **DW** = 1.915063 **Prob(F)** = 0 **t** = -1.98						
Coefficient	BLUESTAR	-13.7697	0.8489	-0.1148	0.5275	0.7692	0.2452	0.1216
Std. Error		3.9782	0.1312	0.1224	0.1324	0.2170	0.0693	0.0373
t-Statistic		-3.4613	6.4712	-0.9377	3.9830	3.5440	3.5352	3.2578
Prob.		0.0010	0.0000	0.3522	0.0002	0.0008	0.0008	0.0019
		R-sq =0.920026 **AdjR-sq** = 0.911893 **DW** = 2.032666 **Prob(F)** = 0 **t** = -3.49						
Coefficient	CMC	-0.0966	0.9879	-0.2086	0.0498	0.0676	-0.0379	0.0000
Std. Error		2.3038	0.1237	0.1321	0.0744	0.1196	0.0354	0.0000
t-Statistic		-0.0419	7.9829	-1.5792	0.6698	0.5654	-1.0714	0.0000
Prob.		0.9667	0.0000	0.1195	0.5055	0.5739	0.2883	0.0000
		R-sq = 0.767065 **AdjR-sq** = 0.747653 **DW** = 1.992401 **Prob(F)** = 0 **t** = -2.35						
Coefficient	COSMO	1.6672	0.5711	0.2725	-0.1187	-0.0414	-0.1666	0.0770
Std. Error		2.0388	0.1227	0.1321	0.1476	0.1018	0.1122	0.0439
t-Statistic		0.8177	4.6535	2.0635	-0.8040	-0.4064	-1.4847	1.7568
Prob.		0.4168	0.0000	0.0435	0.4247	0.6859	0.1429	0.0841
		R-sq = 0.884129 **AdjR-sq** = 0.872346 **DW** = 2.053098 **Prob(F)** = 0 **t** = -1.61						
Coefficient	CREST	10.6456	0.9274	-0.0607	-0.5491	-0.5031	0.1067	0.0000
Std. Error		3.3939	0.1264	0.1347	0.1934	0.1635	0.0868	0.0000
t-Statistic		3.1367	7.3374	-0.4510	-2.8396	-3.0761	1.2297	0.0000
Prob.		0.0026	0.0000	0.6536	0.0062	0.0032	0.2236	0.0000
		R-sq = 0.910739 **AdjR-sq** = 0.903301 **DW** = 2.096961 **Prob(F)** = 0 **t** = -1.99						

Table 1. Contd.

		C	$\ln P_{t-1}$	$\ln P_{t-2}$	$\ln BM$	$\ln MV$	$\ln \beta$	$\ln \beta$ Negative
Coefficient	CYBERSYS	-0.0126	0.9641	0.0101	-0.0026	-0.0038	0.1257	0.0000
Std. Error		0.6056	0.1277	0.1355	0.0988	0.0295	0.1393	0.0000
t-Statistic		-0.0209	7.5490	0.0746	-0.0266	-0.1305	0.9028	0.0000
Prob.		0.9834	0.0000	0.9408	0.9789	0.8966	0.3702	0.0000
		R-sq = 0.950369 **AdjR-sq** = 0.946233 **DW** = 1.960987 **Prob(F)** = 0 **t** = -0.45						
Coefficient	DSQ	7.2462	0.8419	-0.0449	-0.3656	-0.2533	-0.9163	0.0000
Std. Error		2.8389	0.1280	0.1472	0.1305	0.1214	0.3472	0.0000
t-Statistic		2.5525	6.5755	-0.3051	-2.8022	-2.0871	-2.6390	0.0000
Prob.		0.0133	0.0000	0.7613	0.0068	0.0411	0.0106	0.0000
		R-sq = 0.964638 **AdjR-sq** = 0.961691 **DW** = 2.024837 **Prob(F)** = 0 **t** = -2.14						
Coefficient	ESERVE	-24.6422	0.7094	0.1346	0.8987	1.2783	0.9219	3.6217
Std. Error		89.5153	0.1260	0.1303	3.0048	4.4734	3.0649	11.9790
t-Statistic		-0.2753	5.6297	1.0328	0.2991	0.2858	0.3008	0.3023
Prob.		0.7841	0.0000	0.3059	0.7659	0.7761	0.7646	0.7635
		R-sq = 0.744673 **AdjR-sq** = 0.718707 **DW** = 2.00396 **Prob(F)** = 0 **t** = -2.00						
Coefficient	FINOLEX	-16.1226	0.5453	0.1806	0.9429	0.7748	-0.1734	-0.1731
Std. Error		11.0004	0.1225	0.1217	0.4899	0.4941	0.0817	0.0496
t-Statistic		-1.4656	4.4526	1.4832	1.9247	1.5680	-2.1235	-3.4861
Prob.		0.1481	0.0000	0.1433	0.0591	0.1222	0.0379	0.0009
		R-sq = 0.918078 **AdjR-sq** = 0.909747 **DW** = 2.105351 **Prob(F)** = 0 **t** = -3.27						
Coefficient	HCL	47.1060	0.7081	0.1682	-1.9989	-2.1246	-0.0051	-0.3191
Std. Error		63.5441	0.1288	0.1264	2.6236	2.8765	0.6754	0.1115
t-Statistic		0.7413	5.4964	1.3300	-0.7619	-0.7386	-0.0076	-2.8616
Prob.		0.4614	0.0000	0.1886	0.4492	0.4631	0.9940	0.0058
		R-sq = 0.941186 **AdjR-sq** = 0.935205 **DW** = 2.109003 **Prob(F)** = 0 **t** = -1.97						
Coefficient	HINDUJA	-2.3139	1.1041	-0.0711	0.3663	0.1018	-0.0037	0.0000
Std. Error		3.3113	0.1192	0.1426	0.2244	0.1525	0.0142	0.0000
t-Statistic		-0.6988	9.2590	-0.4987	1.6326	0.6672	-0.2606	0.0000
Prob.		0.4874	0.0000	0.6198	0.1078	0.5072	0.7953	0.0000
		R-sq = 0.919182 **AdjR-sq** =0.912448 **DW** = 1.916596 **Prob(F)** = 0 **t** = 0.501						

Table 1. Contd.

		C	$\ln P_{t-1}$	$\ln P_{t-2}$	$\ln BM$	$\ln MV$	$\ln \beta$	$\ln \beta$ Negative
Coefficient	INFOSYS	1.4784	0.7773	-0.0043	-0.1270	0.0027	0.1151	0.0000
Std. Error		0.8466	0.1296	0.1347	0.0858	0.0238	0.0895	0.0000
t-Statistic		1.7462	5.9957	-0.0322	-1.4809	0.1138	1.2857	0.0000
Prob.		0.0859	0.0000	0.9744	0.1439	0.9098	0.2035	0.0000
		R-sq = 0.745948 **AdjR-sq** = 0.724777 **DW** = 1.977954 **Prob(F)** = 0 **t** = -2.46						
Coefficient	JAIN	9.0544	0.8429	-0.0659	-0.8248	-0.4300	-0.2054	0.6225
Std. Error		17.8614	0.1252	0.1217	1.1730	0.9210	0.3371	0.4103
t-Statistic		0.5069	6.7308	-0.5418	-0.7031	-0.4669	-0.6093	1.5171
Prob.		0.6141	0.0000	0.5900	0.4847	0.6423	0.5447	0.1346
		R-sq = 0.888267 **AdjR-sq** = 0.876904 **DW** = 1.962494 **Prob(F)** = 0 **t** = -3.28						
Coefficient	MASTEK	2.2929	0.9542	0.0070	-0.0867	-0.1060	0.1076	0.0000
Std. Error		2.3421	0.1285	0.1367	0.1135	0.1082	0.2299	0.0000
t-Statistic		0.9790	7.4288	0.0510	-0.7638	-0.9791	0.4682	0.0000
Prob.		0.3315	0.0000	0.9595	0.4480	0.3315	0.6414	0.0000
		R-sq = 0.923703 **AdjR-sq** = 0.917345 **DW** = 1.915473 **Prob(F)** = 0 **t** = -0.74						
Coefficient	MOSER	1.2697	0.7552	0.0491	0.0044	-0.0071	0.0154	-0.0662
Std. Error		0.9839	0.1282	0.1286	0.1335	0.0440	0.1054	0.0886
t-Statistic		1.2905	5.8909	0.3814	0.0329	-0.1605	0.1461	-0.7472
Prob.		0.2019	0.0000	0.7043	0.9738	0.8730	0.8844	0.4579
		R-sq = 0.772889 **AdjR-sq** = 0.749793 **DW** = 2.057018 **Prob(F)** = 0 **t** = -2.48						
Coefficient	MPHASIS	5.8226	0.8672	-0.1516	-0.0467	-0.1757	-0.6700	0.0258
Std. Error		2.3446	0.1321	0.1284	0.0407	0.0874	0.3900	0.0206
t-Statistic		2.4834	6.5665	-1.1801	-1.1499	-2.0103	-1.7178	1.2520
Prob.		0.0159	0.0000	0.2427	0.2548	0.0490	0.0911	0.2155
		R-sq = 0.822951 **AdjR-sq** = 0.804946 **DW** = 1.904903 **Prob(F)** = 0 **t** = -2.82						
Coefficient	MTNL	30.4114	0.5738	-0.0237	-0.9100	-1.1147	0.0738	0.1072
Std. Error		8.6277	0.1239	0.1223	0.2506	0.3309	0.0694	0.0684
t-Statistic		3.5248	4.6331	-0.1940	-3.6309	-3.3691	1.0624	1.5673
Prob.		0.0008	0.0000	0.8469	0.0006	0.0013	0.2924	0.1224
		R-sq = 0.797689 **AdjR-sq** = 0.777115 **DW** = 2.02991 **Prob(F)** = 0 **t** = -4.29						

Table 1. Contd.

		C	$\ln P_{t-1}$	$\ln P_{t-2}$	$\ln BM$	$\ln MV$	$\ln \beta$	$\ln \beta$ Negative
Coefficient	NIIT	37.7572	0.7398	-0.0706	-0.2841	-1.4403	0.1576	0.2572
Std. Error		17.3706	0.1260	0.1439	0.1369	0.6851	0.1647	0.1361
t-Statistic		2.1736	5.8692	-0.4907	-2.0754	-2.1022	0.9572	1.8900
Prob.		0.0338	0.0000	0.6255	0.0423	0.0398	0.3424	0.0637
		R-sq = 0.94485 **AdjR-sq** = 0.939241 **DW** = 2.061302 **Prob(F)** = 0 **t** = -2.88						
Coefficient	ORIENT	1.5824	0.9117	-0.0911	-0.1604	-0.0478	0.1549	0.0000
Std. Error		5.0381	0.1274	0.1390	0.2847	0.2450	0.1144	0.0000
t-Statistic		0.3141	7.1576	-0.6551	-0.5635	-0.1951	1.3535	0.0000
Prob.		0.7546	0.0000	0.5149	0.5752	0.8460	0.1810	0.0000
		R-sq =0.842621 **AdjR-sq** = 0.829506 **DW** = 2.041689 **Prob(F)** = 0 **t** = -2.12						
Coefficient	PENTA MEDIA	80.8495	0.8670	-0.0305	-3.8814	-3.4607	-0.3694	0.0000
Std. Error		74.0574	0.1301	0.1436	3.4967	3.2023	0.3318	0.0000
t-Statistic		1.0917	6.6667	-0.2126	-1.1100	-1.0807	-1.1131	0.0000
Prob.		0.2793	0.0000	0.8323	0.2714	0.2841	0.2701	0.0000
		R-sq = 0.889507 **AdjR-sq** = 0.880299 **DW** = 1.973686 **Prob(F)** = 0 **t** = -1.81						
Coefficient	PENTA SOFT	42.5597	0.9719	-0.1393	-1.9722	-1.8103	0.1548	0.0000
Std. Error		17.6679	0.1320	0.1393	0.7937	0.7539	0.0864	0.0000
t-Statistic		2.4089	7.3608	-0.9998	-2.4848	-2.4011	1.7904	0.0000
Prob.		0.0191	0.0000	0.3214	0.0158	0.0195	0.0784	0.0000
		R-sq = 0.973311 **AdjR-sq** = 0.971087 **DW** = 1.9787 **Prob(F)** = 0 **t** = -2.46						
Coefficient	SATYAM	11.2988	0.8385	-0.0095	-0.2587	-0.4213	-0.2877	0.0000
Std. Error		3.0198	0.1246	0.1238	0.0820	0.1132	0.1812	0.0000
t-Statistic		3.7416	6.7269	-0.0765	-3.1557	-3.7213	-1.5879	0.0000
Prob.		0.0004	0.0000	0.9393	0.0025	0.0004	0.1176	0.0000
		R-sq = 0.932581 **AdjR-sq** = 0.932581 **DW** = 2.043714 **Prob(F)** = 0 **t** = -2.79						
Coefficient	TATA ELXSI	3.1207	0.7807	-0.0338	-0.2088	-0.1057	-0.4263	0.0000
Std. Error		16.5873	0.1248	0.1245	0.8106	0.8370	0.1444	0.0000
t-Statistic		0.1881	6.2572	-0.2719	-0.2576	-0.1262	-2.9523	0.0000
Prob.		0.8514	0.0000	0.7867	0.7976	0.9000	0.0045	0.0000
		R-sq = 0.954265 **AdjR-sq** = 0.950454 **DW** = 2.110483 **Prob(F)** = 0 **t** = -3.30						

Table 1. Contd.

		C	$\ln P_{t-1}$	$\ln P_{t-2}$	$\ln BM$	$\ln MV$	$\ln \beta$	$\ln \beta$ Negative
Coefficient	TRIGYN	5.1014	0.8659	-0.0216	-0.4772	-0.2191	0.6190	-0.4417
Std. Error		1.4058	0.1226	0.1272	0.1286	0.0710	0.1904	0.1558
t-Statistic		3.6288	7.0651	-0.1695	-3.7108	-3.0853	3.2506	-2.8347
Prob.		0.0006	0.0000	0.8659	0.0005	0.0031	0.0019	0.0063
		R-sq = 0.925827 **AdjR-sq** = 0.918284 **DW** = 1.862401 **Prob(F)** = 0 **t** = -2.01						
Coefficient	VINDHYA	10.2134	0.7560	0.1513	-0.5290	-0.4552	-0.0021	0.0000
Std. Error		16.0776	0.1258	0.1404	0.7364	0.7422	0.0158	0.0000
t-Statistic		0.6353	6.0078	1.0776	-0.7183	-0.6133	-0.1335	0.0000
Prob.		0.5277	0.0000	0.2855	0.4754	0.5420	0.8943	0.0000
		R-sq = 0.950218 **AdjR-sq** = 0.946069 **DW** = 1.998641 **Prob(F)** = 0 **t** = -1.14						
Coefficient	VISUAL SOFT	-0.0865	1.0204	0.0027	0.0601	0.0001	-0.0317	0.0000
Std. Error		0.2200	0.1178	0.1310	0.0379	0.0000	0.0672	0.0000
t-Statistic		-0.3931	8.6597	0.0203	1.5870	3.5622	-0.4727	0.0000
Prob.		0.6957	0.0000	0.9839	0.1178	0.0007	0.6381	0.0000
		R-sq = 0.966808 **AdjR-sq** = 0.964042 **DW** = 2.098287 **Prob(F)** = 0 **t** = -1.94						
Coefficient	VSNL	0.4430	0.8740	0.0380	-0.0182	0.0002	-0.0757	0.0000
Std. Error		0.2729	0.1240	0.1238	0.0452	0.0001	0.0397	0.0000
t-Statistic		1.6236	7.0269	0.3069	-0.4020	3.1263	-1.9084	0.0000
Prob.		0.1097	0.0000	0.7600	0.6891	0.0027	0.0611	0.0000
		R-sq = 0.948448 **AdjR-sq** = 0.944152 **DW** = 2.055311 **Prob(F)** = 0 **t** = -2.51						
Coefficient	WIPRO	0.8487	0.7051	-0.0615	-0.3749	-0.0029	-13.0883	-0.2825
Std. Error		1.1064	0.1265	0.1186	0.0966	0.0370	3.9657	0.0665
t-Statistic		0.7671	5.5733	-0.5184	-3.8824	-0.0775	-3.3004	-4.2493
Prob.		0.4461	0.0000	0.6061	0.0003	0.9385	0.0016	0.0001
		R-sq = 0.939486 **AdjR-sq** = 0.933332 **DW** = 2.176874 **Prob(F)** = 0 **t** = -4.29						
Coefficient	ZEE	178.2118	0.9230	-0.0969	-7.2948	-7.2614	0.0566	25.5415
Std. Error		83.2149	0.1304	0.1319	3.4017	3.3991	0.1358	12.9240
t-Statistic		2.1416	7.0809	-0.7345	-2.1444	-2.1362	0.4169	1.9763
Prob.		0.0364	0.0000	0.4655	0.0361	0.0368	0.6783	0.0528
		R-sq = 0.876331 **AdjR-sq** = 0.863754 **DW** = 2.090802 **Prob(F)** = 0 **t** = -2.34						

Table 1. Contd.

		C	$\ln P_{t-1}$	$\ln P_{t-2}$	$\ln BM$	$\ln MV$	$\ln \beta$	$\ln \beta$ Negative
Coefficient	ZENITH	-51.1420	0.8431	-0.0389	2.5478	2.6038	0.1519	0.0000
Std. Error		19.6560	0.1306	0.1297	0.9720	0.9964	0.0738	0.0000
t-Statistic		-2.6019	6.4546	-0.2996	2.6213	2.6132	2.0580	0.0000
Prob.		0.0117	0.0000	0.7655	0.0111	0.0113	0.0439	0.0000
		R-sq = 0.892003 **AdjR-sq** = 0.883003 **DW** = 2.004182 **Prob(F)** = 0 **t** = -2.54						
Coefficient	ZENSAR	2.8891	0.7915	-0.0622	-0.0985	-0.0702	-0.5501	0.0000
Std. Error		4.0439	0.1268	0.1214	0.1805	0.2002	0.1680	0.0000
t-Statistic		0.7144	6.2398	-0.5124	-0.5457	-0.3508	-3.2743	0.0000
Prob.		0.4777	0.0000	0.6103	0.5873	0.7270	0.0018	0.0000
		R-sq = 0.94899 **AdjR-sq** = 0.944739 **DW** = 1.821649 **Prob(F)** = 0 **t** = -3.64						

5% critical values for t (59) / t (60) are -2 and +2
1% critical values for t (59) / t (60) are -2.66 and +2.66

Table 2. Wald test of the behavioral inertia model

	ACE	AFTE	BLUESTAR	CMC	COSMO
χ^2	2.7656	3.9371	12.19114	5.534355	2.61965
Prob	0.096308	0.04723	0.00048	0.018647	0.105548
	CREST	CYBERSYS	DSQ	ESERVE	FINOLEX
χ^2	3.971055	0.209232	4.582247	4.009459	10.69559
Prob	0.046289	0.64737	0.032305	0.045246	0.001074
	HCL	HINDUJA	INFOSYS	JAIN	MASTEK
χ^2	3.887571	0.251322	6.0695	10.78742	0.559443
Prob	0.048645	0.616146	0.013754	0.001022	0.454485
	MOSER	MPHASIS	MTNL	NIIT	ORIENT
χ^2	6.188097	7.99686	18.47962	8.347959	4.504282
Prob	0.012861	0.004686	0.000017	0.003861	0.03381
	PENTAMEDIA	PENTASOFT	SATYAM	TATA ELXSI	TRIGYN
χ^2	3.280081	6.073744	7.786176	10.93433	4.051178
Prob	0.070125	0.013721	0.005265	0.000944	0.044141

Table 2. Contd.

	VINDHYA	VISUALSOFT	VSNL	WIPRO	ZEE
χ^2	1.305545	3.78141	6.341178	18.41242	5.486939
Prob	0.253203	0.051825	0.011797	0.000018	0.019159
	ZENITH	ZENSAR			
χ^2	6.467986	13.26933			
Prob	0.010983	0.00027			

Table 3. Bootstrap estimate of the Breusch-Godfrey serial correlation test.

		C	$\ln P_{t-1}$	$\ln P_{t-2}$	$\hat{u}_{t-1}$	$\hat{u}_{t-2}$	lnBM	lnMV	$\ln\beta$	$\ln\beta$Neg
ACE	Avg	2.17	0.78	-0.07	0.01	-0.00	-0.22	-0.11	0.12	
	S.D	13.55	0.02	0.01	0.04	0.04	0.04	0.05	0.05	
AFTE	Avg	4.27	0.81	-0.02	0.00	0.01	-0.17	-0.15	0.16	
	S.D	13.92	0.01	0.01	0.01	0.00	0.00	0.02	0.26	
BLUESTAR	Avg	-19.26	0.74	-0.13	0.00	-0.00	0.73	1.07	0.33	0.16
	S.D	52.29	0.01	0.01	0.05	0.05	0.06	0.14	0.01	0.00
CMC	Avg	-0.37	0.89	-0.25	-0.00	0.00	0.08	0.12	-0.05	
	S.D	25.28	0.01	0.01	0.04	0.04	0.03	0.05	0.00	
COSMO	Avg	1.25	0.52	0.27	-0.00	0.00	-0.10	-0.00	0.00	-0.17
	S.D	8.12	0.01	0.01	0.03	0.02	0.03	0.02	0.03	0.00
CREST	Avg	13.05	0.84	-0.07	0.01	0.00	-0.68	-0.60	0.12	
	S.D	23.49	0.01	0.01	0.02	0.01	0.07	0.05	0.01	
CYBERSYS	Avg	-0.00	0.86	0.04	0.02	0.00	-0.05	0.00	0.19	
	S.D	0.43	0.01	0.01	0.01	0.01	0.01	0.00	0.02	
DSQ	Avg	2.37	0.80	0.09	0.00	0.00	0.05	0.01	0.15	
	S.D	1.64	0.01	0.01	0.01	0.01	0.01	0.00	0.03	
ESERVE	Avg	8.53	0.76	-0.03	0.00	-0.01	-0.44	-0.29	-1.11	
	S.D	9.79	0.01	0.01	0.01	0.01	0.02	0.01	0.13	

Table 3: Contd.

		C	$\ln P_{t-1}$	$\ln P_{t-2}$	$\hat{u}_{t-1}$	$\hat{u}_{t-2}$	lnBM	lnMV	$\ln\beta$	$\ln\beta$Neg
FINOLEX	Avg	-24.12	0.57	0.05	0.03	0.05	0.89	1.30	0.85	3.62
	S.D	472.26	0.02	0.01	0.03	0.03	53.25	117.59	56.40	84.37
HCL	Avg	-26.24	0.41	0.10	0.05	0.02	1.47	1.27	-0.25	-0.25
	S.D	208.24	0.02	0.01	0.1301	0.11	4.03	4.16	0.09	0.03
HINDUJA	Avg	50.05	0.61	0.16	-0.00	-0.01	-2.15	-2.24	0.11	-0.43
	S.D	157.26	0.01	0.01	0.0280	0.03	26.71	32.27	1.71	0.02
INFOSYS	Avg	-3.47	1.01	-0.01	0.02	0.03	0.42	0.16	-0.00	
	S.D	31.63	0.01	0.01	0.02	0.02	0.12	0.06	0.00	
JAIN	Avg	2.36	0.68	-0.05	-0.01	-0.01	-0.17	0.00	0.17	
	S.D	1.26	0.01	0.01	0.02	0.02	0.01	0.00	0.02	
MASTEK	Avg	10.23	0.79	-0.07	-0.00	-0.00	-0.92	-0.48	-0.18	0.69
	S.D	158.96	0.01	0.01	0.00	0.00	0.68	0.42	0.06	0.08
MOSER	Avg	2.91	0.90	-0.00	0.01	0.01	-0.10	-0.11	0.04	
	S.D	1.75	0.01	0.01	0.00	0.00	0.00	0.00	0.02	
MPHASIS	Avg	1.44	0.62	-0.00	0.01	0.04	0.03	0.02	-0.01	-0.10
	S.D	5.40	0.01	0.01	0.03	0.03	0.09	0.01	0.04	0.03
MTNL	Avg	8.17	0.76	-0.17	-0.02	-0.00	-0.07	-0.24	-0.87	0.02
	S.D	13.99	0.01	0.01	0.02	0.02	0.00	0.02	0.22	0.00
NIIT	Avg	39.13	0.47	-0.10	0.00	0.01	-1.19	-1.42	0.09	0.14
	S.D	131.44	0.01	0.01	0.08	0.09	0.49	0.97	0.04	0.04
ORIENT	Avg	45.57	0.65	-0.08	-0.02	-0.03	-0.35	-1.72	0.21	0.27
	S.D	160.38	0.01	0.01	0.02	0.02	0.01	1.03	0.05	0.03
PENTAMEDIA	Avg	0.61	0.82	-0.11	0.00	-0.00	-0.13	0.01	0.21	
	S.D	48.67	0.01	0.01	0.01	0.01	0.14	0.11	0.02	
PENTA SOFT	Avg	81.45	0.86	-0.02	0.00	0.00	-0.38	-3.48	-3.89	
	S.D	366.62	0.00	0.00	0.01	0.01	8.18	6.85	0.08	

Table 3: Contd.

		C	$\ln P_{t-1}$	$\ln P_{t-2}$	$\hat{u}_{t-1}$	$\hat{u}_{t-2}$	lnBM	lnMV	$\ln \beta$	$\ln \beta$Neg
SATYAM	Avg	53.82	0.89	-0.12	0.01	-0.00	-2.51	-2.28	0.19	
	S.D	393.56	0.016	0.01	0.01	0.02	0.75	0.72	0.01	
TATA ELXSI	Avg	14.65	0.76	-0.01	0.00	0.00	-0.34	-0.54	-0.37	
	S.D	20.59	0.01	0.01	0.02	0.02	0.01	0.02	0.08	
TRIGYN	Avg	6.16	0.76	-0.00	-0.00	-0.01	-0.61	-0.25	0.81	-0.58
	S.D	3.30	0.01	0.01	0.01	0.01	0.02	0.00	0.06	0.04
VINDHYA	Avg	8.72	0.65	0.10	0.05	0.01	-0.55	-0.35	-0.00	
	S.D	133.66	0.02	0.01	0.04	0.04	2.70	2.89	0.00	
VISUALSOFT	Avg	27.84	0.78	0.03	0.00	-0.00	-1.18	-1.26	-0.14	
	S.D	45.03	0.01	0.01	0.01	0.01	0.09	0.09	0.00	
VSNL	Avg	-28.21	0.76	-0.02	0.01	-0.00	1.19	1.19	-0.13	
	S.D	406.04	0.01	0.01	0.03	0.03	0.79	0.67	0.00	
WIPRO	Avg	1.04	0.64	-0.06	0.01	0.00	-0.42	-0.00	-14.63	-0.31
	S.D	0.99	0.01	0.01	0.01	0.01	0.00	0.00	12.05	0.00
ZEE	Avg	196.68	0.84	-0.11	-0.00	0.00	-8.05	-7.99	0.05	24.42
	S.D	350.	0.01	0.01	0.00	0.00	5.77	5.87	0.01	122.75
ZENITH	Avg	-68.20	0.75	-0.05	-0.00	-0.00	3.38	3.47	0.21	
	S.D	594.91	0.01	0.01	0.01	0.01	1.50	1.51	0.01	
ZENSAR	Avg	2.80	0.73	-0.05	-0.01	-0.01	-0.09	-0.05	-0.66	
	S.D	18.30	0.01	0.01	0.01	0.01	0.03	0.04	0.03	

Table 4. p values of the Breusch-Godfrey test.

COMPANY NAME	p Value
ACE	0.431
AFTE	0.548
BLUESTAR	0.164
CMC	0.823
COSMO	0.868
CREST	0.510
CYBERSYS	0.193
DSQ	0.655
ESERVE	0.298
FINOLEX	0.189
HCL	0.346
HINDUJA	0.283
INFOSYS	0.779
JAIN	0.734
MASTEK	0.266
MOSER	0.539
MPHASIS	0.219
MTNL	0.756
NIIT	0.129
ORIENT	0.574
PENTAMEDIA	0.797
PENTASOFT	0.382
SATYAM	0.519
TATA ELXSI	0.044
TRIGYN	0.270
VINDHYA	0.737
VISUALSOFT	0.369
VSNL	0.241
WIPRO	0.017
ZEE	0.185
ZENITH	0.966
ZENSAR	0.028

Table 5. Bootstrap estimate of the Behavioral Inertia Model.

		C	lnPt-1	lnPt-2	lnBM	lnMV	lnBeta	lnBetaNeg
ACE	Avg	4.8945	0.8826	0.1170	-0.0867	-0.1464	0.0981	
	S.D	37.4142	0.0115	0.0115	0.0670	0.1203	0.1301	
AFTE	Avg	7.9967	0.8702	0.1292	-0.0293	-0.1067	0.1380	
	S.D	129.5431	0.0099	0.0099	0.2382	0.2580	2.4555	
BLUESTAR	Avg	0.7352	0.9862	0.0133	0.2315	0.2041	0.0730	0.0362
	S.D	511.6248	0.0086	0.0087	1.3187	1.3966	0.0340	0.0118
CMC	Avg	8.6148	1.0556	-0.0557	-0.0076	-0.1144	-0.0182	
	S.D	117.5933	0.0030	0.0031	0.2525	0.2849	0.0056	
COSMO	Avg	5.3513	0.6067	0.3928	-0.0140	-0.0533	0.0014	-0.0853
	S.D	71.0816	0.0091	0.0091	0.1271	0.1983	0.2171	0.0300
CREST	Avg	10.5054	0.9075	0.0920	-0.2196	-0.2957	0.0355	
	S.D	64.3950	0.0099	0.0100	1.1575	0.7203	0.3431	
CYBERSYS	Avg	3.8262	0.9049	0.0922	0.1918	0.0051	-0.0703	
	S.D	8.1706	0.0144	0.0145	0.4842	0.0210	0.6645	
DSQ	Avg	3.8262	0.9049	0.0922	0.1918	0.0051	-0.0703	
	S.D	8.1706	0.0144	0.0145	0.4842	0.0210	0.6645	
ESERVE	Avg	6.9320	0.8287	0.1672	0.0113	-0.1157	0.0597	
	S.D	279.9709	0.0134	0.0137	0.9038	0.5402	4.4876	
FINOLEX	Avg	47.8084	0.7531	0.2459	-1.3273	-2.0970	-4.7479	-2.1662
	S.D	431.0150	0.0057	0.0057	48.4821	17.1825	51.9705	78.8900
HCL	Avg	-5.0334	0.6698	0.3299	0.6350	0.4503	-0.0707	-0.0846
	S.D	211.7950	0.0052	0.0053	3.3074	4.1706	0.0735	0.0202
HINDUJA	Avg	56.1735	0.7395	0.2597	-2.0119	-2.2945	-0.3477	-0.1327
	S.D	103.9660	0.0100	0.0101	170.5978	212.0921	15.9674	0.1322

Table 5: Contd.

		C	lnPt-1	lnPt-2	lnBM	lnMV	lnBeta	lnBetaNeg
INFOSYS	Avg	0.5424	1.0625	-0.0627	0.4816	0.2222	-0.0070	
	S.D	35.2876	0.0092	0.0091	1.2301	0.7612	0.0027	
JAIN	Avg	8.0802	0.8626	0.1371	0.0030	0.0069	0.0898	
	S.D	6.9301	0.0035	0.0036	0.1290	0.0040	0.2239	
MASTEK	Avg	-0.6890	0.9306	0.0685	0.4273	0.3049	0.2874	0.4631
	S.D	254.0420	0.0127	0.0128	10.7869	6.8105	1.9857	1.5527
MOSER	Avg	6.5259	0.9011	0.0983	-0.0172	-0.0760	0.0934	
	S.D	63.8669	0.0152	0.0153	0.1567	0.1390	0.6546	
MPHASIS	Avg	6.1905	0.8276	0.1721	0.0495	-0.0198	0.0180	0.1160
	S.D	109.8987	0.0056	0.0056	0.4837	0.2315	0.2697	0.0602
MTNL	Avg	7.4850	0.9914	0.0083	-0.0065	-0.0517	0.1190	0.0290
	S.D	277.1138	0.0056	0.0057	0.0717	0.5708	0.4020	0.0212
NIIT	Avg	17.1427	0.7904	0.2091	-0.2898	-0.4773	0.0289	0.0364
	S.D	165.7839	0.0035	0.0036	1.2452	0.7477	0.0492	0.0402
ORIENT	Avg	28.4051	0.7960	0.2032	0.0880	-0.8736	0.1197	0.1476
	S.D	189.3990	0.0105	0.0107	0.0971	8.1961	1.0100	0.4530
P MEDIA	Avg	6.3730	0.9151	0.0845	-0.0477	-0.0966	0.0533	
	S.D	405.3555	0.0109	0.0110	0.7345	0.8873	0.3966	
P SOFT	Avg	117.4129	0.8932	0.1051	-1.6598	-4.8580	-3.7574	
	S.D	100.4350	0.0060	0.0065	226.0406	188.1434	0.8461	
SATYAM	Avg	-1.5932	0.9473	0.0511	0.3442	0.2386	0.0893	
	S.D	133.9580	0.0133	0.0133	26.6494	25.3509	0.2870	
TATAELXSI	Avg	10.7679	0.8830	0.1165	-0.0374	-0.1821	-0.1646	
	S.D	100.3901	0.0106	0.0107	0.3010	0.1972	1.2693	

Table 5: Contd.

		C	lnPt-1	lnPt-2	lnBM	lnMV	lnBeta	lnBetaNeg
TRIGYN	Avg	10.8670	0.8607	0.1379	-0.2359	-0.2537	-0.6357	0.5459
	S.D	28.4277	0.0122	0.0123	0.6459	0.0664	3.7402	0.3244
VINDHYA	Avg	7.9584	0.7264	0.2731	-0.1631	-0.1896	-0.0072	
	S.D	480.1230	0.0116	0.0117	9.6575	10.3739	0.0047	
V SOFT	Avg	11.6714	0.8326	0.1648	0.3684	-0.2750	-0.5464	
	S.D	165.2890	0.0140	0.0141	4.3772	3.9263	0.1429	
VSNL	Avg	4.9333	0.9041	0.0952	0.1401	0.0438	0.0229	
	S.D	282.0560	0.0092	0.0092	4.8945	4.5337	0.2014	
WIPRO	Avg	6.7106	0.9100	0.0892	0.0256	-0.0041	1.9091	-4.4758
	S.D	31.4942	0.0048	0.0048	0.5551	0.0217	511.1773	0.1792
ZEE	Avg	79.8572	0.9512	0.0484	-2.9420	-2.9940	0.0161	17.1993
	S.D	501.1256	0.0120	0.0120	82.5244	83.9332	0.2255	231.9700
ZENITH	Avg	11.3456	0.8995	0.0998	1.2931	1.2319	0.1177	
	S.D	694.6900	0.0111	0.0113	16.8880	17.6566	0.6614	
ZENSAR	Avg	4.7382	0.8983	0.1000	0.0836	-0.0120	-0.1225	
	S.D	356.5256	0.0143	0.0144	0.7633	0.8931	0.4144	

Table 6. p values of the Wald test.

COMPANY NAME	p Value
ACE	0.130
AFTE	0.063
BLUESTAR	0.211
CMC	0.053
COSMO	0.193
CREST	0.057
CYBERSYS	0.659
DSQ	0.060
ESERVE	0.232
FINOLEX	0.196
HCL	0.070
HINDUJA	0.638
INFOSYS	0.032
JAIN	0.247
MASTEK	0.434
MOSER	0.211
MPHASIS	0.007
MTNL	0.207
NIIT	0.004
ORIENT	0.070
PENTAMEDIA	0.111
PENTASOFT	0.022
SATYAM	0.011
TATA ELXSI	0.267
TRIGYN	0.075
VINDHYA	0.362
VISUALSOFT	0.071
VSNL	0.027
WIPRO	0.232
ZEE	0.045
ZENITH	0.012
ZENSAR	0.223

APPENDIX 1

Unit root test on $\ln P_t$ series.

	Trend and intercept			Intercept	First Difference
Company Name	ADF Test Statistic	LR statistic	p value	ADFTest Statistic	ADFTest Statistic
ACE	-1.65260	3.01103	0.22190	-1.36177	-4.45132
AFTE	-3.30391	11.79965	0.01011	-2.16278	-3.63110
BLUESTAR	-1.29002	2.97545	0.22589	-0.49399	-3.94376
CMC	-2.22767	5.38762	0.06762	-1.70677	-5.83399
COSMO	-1.81554	5.29531	0.07082	-2.18307	-4.86096
CREST	-2.60502	6.99037	0.03034	-1.61098	-3.87510
CYBERSYS	-1.41327	2.80383	0.24613	-1.31309	-4.65562
DSQ	-2.38188	6.02015	0.04929	-0.51687	-4.46176
ESERVE	-3.55981	15.04889	0.02134	-3.05534	-4.26175
FINOLEX	-1.51209	4.62226	0.09915	-2.05328	-4.59224
HCL	-0.70040	3.50963	0.17294	-0.86471	-3.60139
HINDUJA	-3.28890	11.42558	0.03148	-3.07396	-3.94296
INFOSYS	-2.99447	10.61218	0.02434	-1.64174	-4.65933
JAIN	-1.66241	3.11550	0.21061	-1.53597	-4.47584
MASTEK	-2.01687	4.45127	0.10800	-1.24104	-4.49361
MOSER	-3.58313	14.18448	0.01774	-3.05630	-4.26908
MPHASIS	-2.14019	4.79180	0.09109	-2.10937	-4.97569
MTNL	-2.73524	7.81744	0.02007	-2.09223	-6.78012
NIIT	-1.46158	2.51490	0.28438	-1.27396	-4.66568
ORIENT	-2.71885	7.61819	0.02217	-1.60495	-4.39461
PENTAMEDIA	-1.55242	3.73631	0.15441	-1.89891	-5.10155
PENTASOFT	-2.51994	6.53922	0.03802	-0.69573	-5.02415
SATYAM	-1.88054	4.20752	0.12200	-1.88117	-4.32108
TATAELXSI	-3.19582	11.00724	0.03724	-0.31814	-4.75306
TRIGYN	-1.69345	3.30000	0.19205	-1.61317	-4.01304
VINDHYA	-3.51537	12.24155	0.02929	-0.95324	-5.23041
VISUALSOFT	-1.87475	3.84356	0.14635	-1.17511	-3.64867
VSNL	-2.00977	4.26034	0.11882	-1.15712	-4.29305
WIPRO	-2.02116	4.49261	0.10579	-1.30433	-5.17209
ZEE	-1.87954	4.59670	0.10042	-1.71294	-4.70897
ZENITH	-1.65304	3.09658	0.21261	-1.14573	-5.29169
ZENSAR	-1.85018	4.18838	0.12317	-1.55714	-4.28964

Unit root test on $\ln BM$ series.

	Trend and intercept			Intercept	First Difference
Company Name	ADF Test Statistic	LR statistic	p value	ADF Test Statistic	ADF Test Statistic
ACE	-1.69359	3.35276	0.18705	-1.57227	-4.53970
AFTE	-2.46875	6.42389	0.04028	-1.56533	-4.45216
BLUESTAR	-1.69387	3.44662	0.17848	-1.70587	-4.48791
CMC	-1.89377	4.46987	0.10700	-1.92264	-4.56365
COSMO	-2.31826	5.63905	0.05963	-1.74690	-4.52998
CREST	-2.41144	6.06931	0.04809	-1.25576	-4.48453
CYBERSYS	-2.45441	6.24075	0.04414	-1.09700	-4.53345
DSQ	-2.73121	7.62910	0.02205	-0.79174	-4.70001
ESERVE	-2.35138	6.58005	0.03725	-0.84192	-4.48074
FINOLEX	-2.77535	8.07589	0.01763	-1.08523	-4.95558
HCL	-1.98408	4.34250	0.11404	-1.34830	-4.60665
HINDUJA	-2.40410	6.46972	0.03937	-2.27267	-4.51057
INFOSYS	-1.99117	4.18449	0.12341	-1.27988	-4.50575
JAIN	-1.61597	3.03424	0.21934	-1.43957	-4.49499
MASTEK	-2.52801	6.89768	0.03178	-0.90305	-4.56252
MOSER	-1.58385	2.96977	0.22653	-1.43327	-4.45668
MPHASIS	-1.39026	4.30145	0.11640	-1.65237	-4.44764
MTNL	-2.60752	6.99881	0.03022	-0.92930	-4.60236
NIIT	-1.43463	2.83058	0.24286	-1.36106	-4.67975
ORIENT	-2.46106	6.27813	0.04332	-1.48221	-4.47746
PENTAMEDIA	-1.45388	2.89420	0.23525	-1.62594	-4.43765
PENTASOFT	-2.05325	4.41817	0.10980	-1.16089	-4.49689
SATYAM	-2.23658	5.21641	0.07367	-1.25882	-4.48835
TATAELXSI	-2.11472	5.03950	0.08048	-0.64671	-4.61062
TRIGYN	-1.94517	4.22251	0.12109	-2.02192	-4.44561
VINDHYA	-2.65490	7.29549	0.02605	-1.03260	-4.78718
VISUALSOFT	-2.53894	6.98864	0.03037	-0.85833	-4.51874
VSNL	-2.32218	6.08525	0.04771	-1.60426	-4.43571
WIPRO	-2.78966	7.94784	0.01880	-0.69646	-4.80392
ZEE	-1.43791	3.22202	0.19969	-1.42894	-4.47237
ZENITH	-1.77276	3.40941	0.18183	-1.77333	-4.44255
ZENSAR	-2.73857	7.66177	0.02169	-0.86790	-4.73398

Unit root test on $\ln MV$ series.

	Trend and intercept			Intercept	First Difference
Company Name	ADF Test Statistic	LR statistic	p value	ADFTest Statistic	ADFTest Statistic
ACE	-2.36305	5.78711	0.05538	-1.05200	-4.58942
AFTE	-2.44668	6.56535	0.03753	-2.39192	-4.43803
BLUESTAR	-1.78896	3.66209	0.16025	-1.82017	-4.43471
CMC	-1.93344	4.36729	0.11263	-1.90081	-4.43807
COSMO	-2.31318	5.66261	0.05894	-1.38163	-4.58803
CREST	-2.49494	6.70790	0.03495	-1.37317	-4.45677
CYBERSYS	-2.11083	4.70272	0.09524	-1.75451	-4.44177
DSQ	-2.51793	6.67853	0.03546	-0.69785	-4.60052
ESERVE	-2.12859	6.03391	0.04895	-2.42819	-4.50805
FINOLEX	-2.97142	9.08200	0.01066	-0.95382	-5.02213
HCL	-1.91776	4.07852	0.13013	-1.40748	-4.56803
HINDUJA	-2.34031	6.40378	0.04069	-2.15568	-4.56581
INFOSYS	-1.83477	3.57577	0.16731	-1.44491	-4.45680
JAIN	-1.60634	2.95557	0.22814	-1.59142	-4.48169
MASTEK	-2.52703	6.89845	0.03177	-1.10495	-4.49163
MOSER	-2.29033	5.51792	0.06336	-1.38008	-4.66497
MPHASIS	-1.63825	3.17826	0.20410	-1.25233	-4.47385
MTNL	-2.57356	6.95845	0.03083	-1.11632	-4.50294
NIIT	-1.69817	4.00601	0.13493	-1.33388	-4.44734
ORIENT	-2.50661	6.61590	0.03659	-1.34249	-4.46998
PENTAMEDIA	-1.44896	2.87831	0.23713	-1.63038	-4.43866
PENTASOFT	-2.04630	4.39523	0.11107	-1.23992	-4.47348
SATYAM	-2.37427	6.03959	0.04881	-1.72643	-4.43776
TATAELXSI	-2.04978	4.85137	0.08842	-0.67812	-4.58112
TRIGYN	-2.13890	4.78138	0.09157	-1.34824	-4.47360
VINDHYA	-2.76691	7.82651	0.01998	-0.92836	-4.77324
VISUALSOFT	-2.48565	6.84418	0.03264	-1.01998	-4.48183
VSNL	-2.34276	6.10152	0.04732	-1.56124	-4.43741
WIPRO	-2.04509	6.00026	0.04978	-1.74205	-4.43578
ZEE	-1.44698	3.15735	0.20625	-1.42122	-4.47290
ZENITH	-1.69795	3.21729	0.20016	-1.68868	-4.44177
ZENSAR	-2.56653	6.93208	0.03124	-0.81016	-4.63077

Unit root test on $\ln \beta$ series.

	Trend and intercept			Intercept	First Difference
Company Name	ADF Test Statistic	LR statistic	p value	ADF Test Statistic	ADF Test Statistic
ACE	-2.11284	4.70030	0.09536	-1.67338	-4.55389
AFTE	-2.38496	6.30071	0.04284	-2.47489	-4.45580
BLUESTAR	-1.98758	4.14948	0.12559	-1.93059	-4.46930
CMC	-2.00279	4.89370	0.08657	-1.09400	-4.47875
COSMO	-2.07642	5.08610	0.07863	-1.98368	-4.44652
CREST	-1.77724	3.77483	0.15146	-0.76894	-4.55766
CYBERSYS	-2.08732	4.56002	0.10228	-2.02711	-4.43495
DSQ	-1.93612	4.00997	0.13466	-1.52708	-4.47052
ESERVE	-1.83253	5.33535	0.06941	-2.25853	-4.52630
FINOLEX	-2.27136	5.76365	0.05603	-1.60670	-4.43536
HCL	-1.92159	3.96533	0.13770	-1.01602	-4.57807
HINDUJA	-1.83675	3.62973	0.16286	-1.28300	-4.52444
INFOSYS	-1.87919	3.73295	0.15467	-1.72998	-4.47579
JAIN	-2.01351	4.42086	0.10965	-0.67929	-4.67184
MASTEK	-1.92160	4.24993	0.11944	-1.99547	-4.44256
MOSER	-1.81387	5.77913	0.05560	-1.83557	-4.44790
MPHASIS	-1.85829	4.04470	0.13234	-1.89884	-4.43766
MTNL	-2.42502	6.13622	0.04651	-1.95760	-4.45237
NIIT	-2.04686	4.56539	0.10201	-0.84458	-4.60406
ORIENT	-2.33023	5.96121	0.05076	-2.31915	-4.50024
PENTAMEDIA	-2.17161	5.49386	0.06413	-1.65162	-4.63400
PENTASOFT	-2.25219	6.01159	0.04950	-2.12984	-4.43507
SATYAM	-1.94196	3.96829	0.13750	-1.95294	-4.43946
TATAELXSI	-1.82140	3.55780	0.16882	-1.09463	-4.56911
TRIGYN	-1.94429	4.19842	0.12255	-1.15255	-4.48242
VINDHYA	-1.78388	3.92688	0.14038	-0.69949	-4.55546
VISUALSOFT	-1.74860	3.27673	0.19430	-1.72157	-4.43471
VSNL	-2.34514	6.22010	0.04460	-2.30598	-4.52773
WIPRO	-1.90340	4.41190	0.11015	-0.58659	-4.58258
ZEE	-1.65334	3.72324	0.15542	-1.15884	-4.46276
ZENITH	-1.47025	4.16833	0.12441	-1.88091	-4.82715
ZENSAR	-1.33018	3.28186	0.19380	-1.77565	-4.51317

Unit root test on $\ln \beta$ negative series.

	Trend and intercept			Intercept	First Difference
Company Name	ADF Test Statistic	LR statistic	p value	ADF Test Statistic	ADF Test Statistic
BLUESTAR	-1.576960	2.942952	.229586	-1.60524	-4.4406
COSMO	-2.31972	5.79885	0.05506	-1.90693	-4.43471
ESERVE	-2.14250	4.88978	0.08674	-0.62444	-4.66881
FINOLEX	-1.98384	5.82460	0.05435	-2.36461	-4.58258
HCL	-1.90340	4.41190	0.11015	-0.58659	-4.58258
JAIN	-1.76113	3.34507	0.18777	-1.74990	-4.43471
MOSER	-1.83529	3.76599	0.15213	-1.90693	-4.43471
MPHASIS	-2.29146	5.64263	0.05953	-1.93064	-4.43479
MTNL	-1.83529	3.76599	0.15213	-1.90693	-4.43471
NIIT	-1.83529	3.76599	0.15213	-1.90693	-4.43471
TRIGYN	-1.83529	3.76599	0.15213	-1.90693	-4.43471
WIPRO	-2.00838	4.43144	0.10908	-1.56294	-4.44202
ZEE	-1.98384	5.82460	0.05435	-2.36461	-4.58258

ADF Critical values for the regression with trend and intercept, intercept (level), and intercept (first difference)

Critical Value*	Trend and intercept	Intercept	First Difference
1%	-4.1035	-3.5328	-3.5345
5%	-3.4790	-2.9062	-2.9069
10%	-3.1669	-2.5903	-2.5907

APPENDIX 2

Breusch-Godfrey Serial Correlation Test.

Company	LM Statistic	Prob	Company	LM Statistic	Prob.
ACE	2.02398	0.363496	MPHASIS	2.7392	0.254206
AFTE	2.5602	0.278009	MTNL	0.23296	0.890049
BLUESTAR	3.28626	0.193374	NIIT	4.44429	0.108377
CMC	0.6762	0.713122	ORIENT	0.83439	0.65889
COSMO	0.9238	0.630086	PENTAMEDIA	0.71662	0.69886
CREST	3.72375	0.155381	PENTASOFT	2.52272	0.28327
CYBERSYS	3.273	0.19466	TATA ELXSI	2.8151	0.24474
DSQ	1.19743	0.549519	VINDHYA	0.83592	0.65839
ESERVE	3.31789	0.19034	VISUALSOFT	2.99735	0.22343
FINOLEX	2.9755	0.22588	VSNL	2.48095	0.28925
HCL	2.1522	0.340922	WIPRO	1.99236	0.36929
HINDUJA	0.7686	0.680927	ZEE	3.2119	0.2007
INFOSYS	0.46836	0.791218	ZENITH	0.26152	0.87743
JAIN	0.26538	0.875737	ZENSAR	1.80806	0.40494
MASTEK	2.97329	0.22613			
MOSER	3.42704	0.18023			

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