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PREDICTION OF STOCK RETURNS USING CLASSICAL AND INTELLIGENT TECHNIQUES: EVIDENCE FROM BSE SENSEX

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This paper is an attempt to predict stock returns using classical (AR) and intelligent (ANN) techniques. AR and ANN techniques are also used to test the efficient market hypotheses using long time-series of daily data of BSE Sensex for the period of January 1997 to September 2005. An attempt has also been made to compare the predictive power of autoregressive (AR) model and artificial neural network (ANN). The present study shows that to a large extent stock market returns are predictable. Profitable investment decisions may be taken using linear and nonlinear techniques of prediction. Prediction improves by using ANN over AR model. Investment decisions based ANN prediction performs better compared to AR prediction. It is observed from the obtained result that MSE and RMSE decrease as the number of observations in training set increases. This is equally applicable to both linear and non-linear (ANN) modeling. The present study does not support efficient market hypotheses.

JEL Classification: G-12, G-14, C-45, C-53.

Key Words: Efficient Market Hypotheses, BDS Test; Artificial Neural Network, Backpropogation.

I. INTRODUCTION

Over the last few decades, there has been much research directed at understanding and predicting the future. Prediction of stock prices is an important issue in investor's investment strategy. Stock prices are predictable only in inefficient stock market. The term efficiency is used to describe a market in which relevant information is not impounded into the price of financial assets. If capital markets are sufficiently competitive, then simple microeconomics indicates that investors cannot expect to achieve superior profits from their investment strategies. Further, it is important for markets to be efficient for optimal resource allocation in the economy between firms and industries. Fama (1970) and Baumol (1965) highlighted the importance of market efficiency in resource allocations in the economy. While there is no conclusive position between practitioners and academicians about the efficiency of stock markets, the prevalent view in economic literature that stock markets are efficient has been dismissed by recent empirical work using both classical and intelligent techniques. Analysing studies covering different stock markets, Fama (1991), says that research is able to show confidently that daily and weekly returns are predictable from past returns. Fama (1998) further points that recent studies on long-term returns suggest market inefficiency, specifically long term underreaction or overreaction to information.

Before the advent non-linear dynamics, statistical test for random walk were usually conducted by verifying that there is no linear dependence between returns and its lagged values. Traditionally, popular classical prediction techniques include regression analysis, time-series analysis, moving averages and smoothing methods, and numerous judgmental methods. However, all of these have the same drawback insofar as they require assumptions about the form of population distribution. Regression models, for example, assume that the underlying population is normally distributed. Outliers can lead to biased estimates of model parameters in classical techniques (Iman and Conover, 1983). The linearity assumption has been conveniently used, because coefficient estimates from linear models are easy to interpret. However, lack of linear dependence did not rule out nonlinear dependence, the presence of which would negate the efficient market hypotheses. Therefore many test are inappropriate, and some conclusions are questionable.

Recent advances in computing technology have relaxed the constraint on computation a bit and have led to the development of non-linear techniques such as Markov regime-switching regression, artificial neural network, genetic algorithm, etc. The non-linear methods in finance can be viewed as an attempt to structure of dependence among variables of interest. Among these methods, there is a general function approximation technique that mimics the functioning of the brain known as the artificial neural network (ANN) method. Artificial Neural Network (ANN) is a member of intelligent techniques, which do not necessarily require assumptions about population distribution. Many have argued that neural networks can overcome or, at least, be less subject to theses limitations (Connor, 1988;Hornik et al., 1989; Wasseman, 1989; White, 1992).Neural networks have been mathematically shown to be universal approximators of functions (Cybenko, 1989; Funahashi, 1989, Hornik *et al.*, 1989) and their derivatives (White et al., 1992). They also can be shown to approximate ordinary least squares and nonlinear least squares regression(White and Stinchcombe, 1992), nonparametric regression(White, 1992), and Fourier series analysis (White and Gallant, 1992).

Not only that ANN do not require assumptions about the underlying population but are also powerful forecasting tools that draw on the most recent developments in artificial intelligence research. Financial modeling using neural networks has gained ground in recent years (Abhyankar, et al., 1997; Gencay, 1999). ANN have found increasing consideration in forecasting theory, leading to successful applications in time series and explanatory sales forecasting (Bishop, 1995; Thiesing and Vornberger,1997). In stock market, prediction is a prerequisite for all investment decisions. Therefore, the quality of a forecast must be evaluated considering its ability to enhance the quality of the investment decision.

In view of this, the present study attempts to predict stock returns using classical and intelligent techniques. Autoregressive techniques are used from classical techniques while Artificial Neural Network is used from intelligent techniques to predict the daily BSE Sensex returns and thereby testing the efficient market hypotheses using data from India's oldest stock market. BDS test is applied to detect the nonlinearities in the series of stock returns. An attempt has also been made to compare the predictive power of autoregressive (AR) model and artificial neural network (ANN). Further, predictive performance of linear AR and non-linear ANN over different time horizon has been compared.

The remaining paper is organized as follows: Section 2 deals with data, Section 3 describes the methodology used, Section 4 analyses the empirical results and finally, Section 5 summarizes the findings and discusses policy implications.

II. DATA

In the present study we used a long time-series of daily data of BSE Sensex (bseindia.com) for the period of January 1997 to September 2005. The present paper has taken the returns on the BSE Sensex as an indicator for analyzing the dependence in the return series. The daily returns have been estimated as follows:

Sensex Daily Returns (R)= log (Sensex close on day t/Sensex close on day t-1) x 100

Further, the return series is normalized between 0 and 1.

Wide ranges of descriptive statistics for the stock index return of the Sensex are shown in Table 1. The sample moments indicate that the empirical distributions of returns are all skewed and highly leptokurtic when compared with normal distributions. This is reinforced by the highly significant Jarque-Bera statistics. Q-statistics(25) indicate the possibility of linear dependence in the series.

Table 1
Preliminary Investigation

Statistics	*R*
Mean	0.501141
Median	0.503912
Maximum	0.833333
Minimum	0.041825
Std. Dev.	0.063020
Skewness	-0.322745
Kurtosis	6.638150
Jarque-Bera	1143.422
Probability	0.000000
Q-Stat(25)	62.147
Probability	0.000000
PP Test Statistics	-41.71172
ADF Test Statistics	-19.43012

Note: MacKinnon critical values for rejection of hypothesis of unit root test (PP Test Statistics, ADF Test Statistics) at 1% are -3.4377, -3.4418, -3.4418 for sample size.

III. METHODOLOGY

For any time series analysis, series must be stationary (Enders, 1995). Stationarity condition has been tested using Augmented Dickey Fuller (ADF) and Phillips-Perron (PP) tests (Dickey and Fuller, 1979, 1981; Phillips and Perron, 1988). While the ADF test corrects for higher order serial correlation by adding lagged differenced terms on the right-hand side, the PP test makes a correction to the t-statistic of the coefficient from the AR (1) regression to account for the serial correlation in error term (u_t). The advantage of Phillips-Perron test is that it is free from parametric errors. Phillips-Perron (PP) test allows the disturbances to be weakly dependent and heterogeneously distributed. In view of this, PP test has also been applied to test for stationarity.

1. Autoregresive (AR) Model

To detect linear dependence in return series, AR Model is estimated using lagged values of stock returns. The number of lags is chosen on the basis of AIC criteria. The AR equation is defined as

$$R_t = \beta_0 + \beta_1 R_{t-1} + \beta_2 R_{t-2} + - - - - - - + \beta_k R_{t-k} + u_t \quad (1)$$

where R_t is normalized stock returns. Ordinary least square method has been used to estimate the equation and t-test is applied to test the null hypotheses of no linear dependence between its lagged values.

2. The Ljung and Box Q-Statistic

The Q-statistic can be used to test whether a group of autocorrelations is significantly different from zero. Ljung and Box (1978) used the sample autocorrelations to form the statistic

$$Q_{LB} = n(n+2)\sum_{k=1}^{m}\left(\frac{\hat{I}_k^2}{n-k}\right) \sim \chi_m^2 \quad (2)$$

where $\hat{I}_k$ stands for Autocorrelation function.

Under $H_0 : I_1 = ... = I_k = 0,:$, Q-statistic asymptotically follows the χ_m^2 distribution with m degrees of freedom. The logic behind the use of this statistic is that high sample autocorrelations lead to large values of Q. If the calculated value of Q exceeds the critical χ_m^2, we can reject the null hypothesis of no significant autocorrelations. Rejection indicates predictability of the series.

3. BDS Test: A Test for Non linearity

The BDS test, named after Brock, Dechert, and Scheinkman (1987), is a statistical version of the correlation dimension test for randomness or "whiteness" against the alternative general dependence in a series. This test for independence is based on estimation of correlation integrals at various dimensions. It has power against all types of linear and non-linear departure. BDS can be interpreted as a test for nonlinearity, if it is used in conjunction with Autoregressive Moving Average (ARMA) modeling. The estimation of the BDS statistic is non-parametric and the test statistic asymptotically follows a normal distribution with zero mean and unit variance.

The intuition behind the test is following:

Let Y_t be a univariate time series, independent and identically distributed from some distribution. Also, define

$$P_A = P(|Y_t - Y_t| < \varepsilon) \quad (3)$$

as the probability that two points are within a distance ε of each other. Further, let us define

$$P_B = P(|Y_t - Y_s| < \varepsilon, |Y_{t-1} - Y_{s-1}| < \varepsilon) \quad (4)$$

as the probability of a history of two observations being within distance ε *of* each other. Under independence of X_t, the two events contained in the event B are independent, and therefore $P_B = P_A^2$. One can estimate and P_A, and P_B and also $P_B - P_A^2$, which has an expected value of zero under the null hypothesis. To estimate the probability that two *m* length vectors are within ε define

$$c_{m,n}(\varepsilon) = \frac{2}{(n-m+1)(n-m)} \sum_{s=m}^{n} \sum_{t=s+1}^{m-1} \prod_{j=0}^{m-1} I_{\varepsilon}(Y_{s-j}, Y_{t-j}) \tag{5}$$

where

$$I_{\varepsilon}(Y_{s-j}, Y_{t-j}) = \begin{cases} 1 ----- If \left|Y_t - Y_t\right| < \varepsilon \\ 0 ----- Otherwise \end{cases} \tag{6}$$

n is the sample size, and m is the so-called embedding dimension. Under the null of independence and identical distribution,

$$E(c_{m,n}(\varepsilon)) = (E(c_{1,n}(\varepsilon)))^m \tag{7}$$

Brock *et al.* (1996) show that, given an embedding dimension, *m* and a value of the radius ε, the BDS statistic

$$w_{m,n}(\varepsilon) = \sqrt{n-m+1} \frac{(c_{m,n}(\varepsilon) - c^{m}_{1\ ,n-m+1}(\varepsilon)}{\sigma_{m,n}(\varepsilon)} \tag{8}$$

asymptotically distributed *N(0, 1)*. The consistent estimator is

$$\sigma^2_{m,n}(\varepsilon) = 4\left[k^m + 2\sum_{j=1}^{m-1} k^{m-j} c^{2j} + (m-1)^2 c^{2m} - m^2 k c^{2m-2}\right] \tag{9}$$

where

$$c = c_{l,n}(\varepsilon) \tag{10}$$

$$k = k_n(\varepsilon) = \frac{6}{n(n-1)(n-2)} \sum_{t=1}^{n} \sum_{s=t+1}^{n} \sum_{r=s+1}^{n} h_e(Y_t, Y_s, Y_r) \tag{11}$$

$$h_e(i,j,k) = \frac{1}{3}\left[I_e(i,j)I_e(j,k) + I_e(i,k)I_e k, j) + I_e(j,i)I_e(i,k)\right] \tag{12}$$

The consistent estimators $c_{1,n}$ (ε) and k_n(ε) are in the class of U statistics and, as it is pointed out by Kanzler (1999), they are the most efficient estimators of *c* and *k,* respectively. Moreover, the test is two-sided, therefore the null hypothesis of independence and identical distribution is rejected at the 5% level if $\left|w_{m,n}(\varepsilon)\right|$ > 1.96.

4. The ANN Framework

The artificial model of the brain is known as Artificial Neural Network (ANN) or simply Neural Networks (NN). In this work, multilayer ANN (MLANN) has been used in predicting the stock returns. MLANN models are non-linear neural network models that can be used to approximate almost any function with a high degree of accuracy (White 1992). An MLP contains a hidden layer of neurons that uses non-linear activation functions, such as a logistic function. The complexity of the MLP can be adjusted by varying the amount of hidden layers. Different amounts of hidden layers can transform an MLP from a simple parametric model to a flexible non-parametric model (White, 1992; Kuan and White, 1994; Fine, 1999; Husmeier, 1999). The number of inputs and outputs in the MLP can be manipulated to analyze different types of data. In this MLANN, number of neurons in the input layer is equal to the no of inputs which is number of lags (past stock returns), whereas, number of output neuron is equal to one. Therefore, proposed network is a multi input and single output network.

The ANN mode most often used in asset price prediction, and the one this study adopts, is a single hidden layer single-output feedforward network of the form:

$$y = \phi_0 + \sum_{h=1}^{H} \phi_h g\left(\sum_{j=1}^{J} \alpha_{hj} x_j \right) \tag{13}$$

where y is the output of the model. There are J inputs represented by x_j . $g(.)$ is known as the activation function of the hidden layer. This may be specified in a number of ways. This study has taken logistic function form, i.e.,

$$g(z) = \frac{\exp(z)}{1+\exp(z)} \tag{14}$$

The network has H neurons in the hidden layer with connection strengths shown by the layer weights, ϕ_h. All inputs enter as arguments in these neurons and their influence are measured by the input weights, α_{hj}. After choosing the type of activation function and specifying the inputs and the number of neurons, the network is trained using backpropagation algorithm. This algorithm appears to be the fastest method for training moderate-sized feedforward neural networks.

ANN Training and Forecast Evaluation

One of the problems that occur during neural network training is called overfitting. The error on the training set is driven to a very small value, but when new data is presented to the network the error is large. The network has memorized the training examples, but it has not learned to generalize to new situations. For improving network generalization, early stopping method has been used. In this technique the available data is divided into three subsets. The first subset is the training set, which is used for computing the gradient and updating the network weights and biases. The second subset is the validation set. The error on the validation set is monitored during the training process. The validation error will normally decrease during the initial phase of training, as does the training set error. However, when the network begins to over fit the data, the error on the validation set will typically begin to rise. When the validation error increases for a specified number of iterations, the training is stopped, and the weights and biases at the minimum of the validation error are returned. Test vectors are used as a further check whether the network is generalizing well.

In this case, we normalized the whole data set between 0 and +1 so that convergence problems are avoided. The sigmoid transfer function is used for hidden units in the hidden layer and the linear transfer function is used for output units in the output layer. To gauge the performance of the models, in-sample and out-of-sample forecasts statistics are computed using several statistics such as, Mean Square Error(MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), MAD, DA, Correlation and Akaike Information Criterion (AIC). These statistics are calculated as:

$$MSE = \frac{1}{n}\sum_{i=1}^{N}(y-\hat{y})^2 \quad (17)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{N}(y-\hat{y})^2} \quad (18)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{N}\left|y-\hat{y}\right| \quad (19)$$

$$MAD = median(\left|u_i - median(\hat{u}_i)\right| \quad (20)$$

where $u_i = (y-\hat{y})$ are the forecasted error values.

$$DA = \frac{1}{n}\sum_{i=1}^{N}a_i \quad (21)$$

$$a_i = \begin{cases} 1 --- if\,(y_{i+1}-y_i)(\hat{y}_{i+1}-y) > 0 \\ 0 --- otherwise \end{cases}$$

$$CORR = \frac{\sum_{i=1}^{N}(y_i-\bar{y})(\hat{y}_i-\bar{\hat{y}})}{\left[\sum_{i=1}^{N}(y_i-\bar{y})^2\sum_{i=1}^{N}(\hat{y}_i-\bar{\hat{y}})^2\right]^{1/2}} \quad (22)$$

IV. EMPIRICAL ANALYSIS

In order to examine the elementary data properties and to test the distribution of series the preliminary investigation of BSE normalized returns (*R*) are presented in Table-1. The results indicate skewed and leptokurtic frequency distribution of return series are not normal. Jarque-Bera test also rejects the null hypothesis of normal distribution for the series. Ljung-Box (Q) test rejects the joint null hypothesis of zero autocorrelations at 1% level, indicating the presence of linear structure in the data. The BSE normalized returns series are found to be stationary as depicted by ADF and PP tests statistics.

1. Auto Regression (AR) Results

As indicated by Ljung-Box (Q) test, we applied AR model to estimate the linear structure in the normalized returns. The lags in AR model are chosen on the basis of AIC criteria. AR moderl is estimated using 1500, 1800, 1900 and 2000 observations, namely AR-1500, AR-1800, AR-1900 and AR-2000. The results are presented in table-2. The AR (9) in all four models captures the linear structure in the normalized return series. The number of lags is chosen on the basis of AIC criteria. The F- test statistics are significant showing the overall significance of the regression results. Durbin-Watson statistics accept the null hypotheses of no autocorrelation. Out of nine lags, AR(1), AR(6) AND AR(9) are found to be significant at 5 per cent level of significance while t-statistics of AR(2), AR(3), AR(4), AR(5), AR(7) and AR(8) are either greater than unity or closer to 1, implying significant effect on F-statistics as per Klien thumb rule. To diagnose the presence of linear structure in AR residuals, Ljung-Box (Q) statistics up to 25 lags are estimated and presented in table 3. The results indicate that there is no remaining linear structure in the AR residuals. The parameter estimate of first three AR model are used for forecasting the remaining observations. The evaluation statistics for the static[1] forecasted results are given in table-4. The MSE, RMSE and MAE in AR-1800 model is minimum.

3. BDS Test: A Test for Non linearity

AR model is capable of finding linear patterns that exist in the data set, but has no ability to trace non-linear patterns that might exist. Having this in mind we apply the BDS test in order to check the non-linearties in residuals produced by the in sample observations. The residual generated by all four AR regressions are tested for non-linearties. In view of similar results and for the brevity of space, the BDS results only for AR-2000 regression are presented in table 5.

The data is exposed to the computational procedure of the correlation integral allowing for five embedding dimensions *m* (2-6) and distances å ranging over the interval 0.5ó-2ó in equal increments. The result shows the evidence of nonlinear association in the AR return series residuals because BDS statistics is significant at 1 percent level of significance. Hence, null hypothesis of IID data-generating process for the BDS test is rejected. These results, therefore, lead us to propose the use of nonlinear modeling. In this light, ANN has been applied.

4. Artificial Neural Network

In this work, we are having 2000 observations, which have been divided into three sets, namely training data set, validation data set and testing data set. Total observations are divided among these three sets in three different ways. In first case, 1000 observation are used for training, 500 observations for validation and 500 observations has been used for testing the performance of network. The results are presented in table 6. In the second case, 1600 observation are used for training, 200 observations for validation and 200 observations has been used for testing the performance of network. The results are presented in table 7. Similarly in third case, 1800 observation are used for training, 100 observations for validation and 100 observations has been used for testing the performance of network. The results are presented in table 7.

In all three cases, lagged values of normalized returns ranging from 4 to 15 are taken as the inputs for the neural network. As far as number of neurons in hidden layer is concerned, we took different number of hidden layer neurons in different cases, namely 3, 4, 8, 12 and 16. Therefore, from the point of view of the number of hidden neurons we are having five different networks. Now we have twelve different training sets, thus yielding a total of sixty different networks to experiment with. Mean Square Error (MSE) is chosen as the cost function and network is selected on the basis of minimum MSE. The results for best performing networks[2] training set, validation set and testing set for all three cases are presented in table 6-8.

In addition to mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE), median absolute deviation (MAD), Pearson correlation coefficient (Corr) and its P-value, direction accuracy (DA) and Akaike information criterion (AIC) have been used to evaluate the predictive power of network. In-sample performance of ANN for training data set, it is observed that performance generally increases with more hidden layers corresponding to each input node. In all 540 neural networks, the study found significant correlation between actual and predicted returns. Obtained results reveal that the change in direction of predicted returns and actual returns are correct approximately in the range of 71 to 75 per cent cases.

Looking at case 1, the neural network with 13 input nodes and 12 hidden layers () depicts best performance on the basis of MSE, MAE, RMSE, DA, Correlation and AIC. . The values of this network of MSE, MAE, RMSE, MAD, DA, Corr. And AIC are 0.0048, 0.0526, 0.0690, 0.0424 0.327, 73.73% and (-) 5321 respectively. Out of sample performance of ANN using validation data set of 500 observations, the performance of architecture is found to be better on the basis of MSE, MAE, RMSE, DA, and Correlation and AIC is highest in case of. For network, the values of MSE, MAE, RMSE, MAD, DA, Corr. And AIC are 0.0021, 0.0346, 0.0462, 0.0261, 0.1913, 58.18 and (-) 3064 respectively. Testing the performance of neural network using testing data set of 500 observations, the neural network architecture consisting of seven input nodes and 12 hidden layers () seems to be performing better on all grounds. The values of this network of MSE, MAE, RMSE, MAD, DA, Corr. And AIC are 0.0028, 0.0388, 0.0527, 0.0309, 0.3147, 51.70 and (-) 2930 respectively (table 6).

In sample performance of case 2, the neural network with 12 input nodes and 16 hidden layers ($NN_{12\times16}$) depicts best performance on the basis of MSE, MAE, RMSE, DA, Correlation and AIC. The values of this network of MSE, MAE, RMSE, MAD, DA, Corr. And AIC are 0.0036, 0.0449, 0.0601, 0.0346, 0.3802, 73.55% and (-) 8975 repectively. Out of sample performance of ANN using unseen validation data set of 200 observations, the performance of $NN_{7\times3}$ architecture is found to be better on the basis of MSE, MAE, RMSE, DA, Correlation and AIC. The values of MSE, MAE, RMSE, MAD, DA, Corr. and AIC are 0.0039, 0.0439, 0.0627, 0.0319, 0.4113, 54.27% and (-)1094 respectively. In all network for validation data, the study found significant correlation between actual and predicted returns. Evaluating the performance of neural network using unseen testing data set of 200 observations, the network consisting of fifteen input nodes and 12 hidden layers ($NN_{15\times12}$) seems to be performing better on all performance evaluating criteria. MSE, MAE, RMSE, MAD, DA, Corr. and AIC in this network is 0.0013, 0.0293, 0.0367, 0.0273, 0.2611, 57.29% and (-) 1292 respectively (table 7).

In case 3, the network consist of 12 input nodes and 16 hidden layers ($NN_{13\times16}$) depicts best performance on the basis of performance criteria. Out of sample performance of ANN using unseen validation data set of 100 observations, the performance of $NN_{9\times8}$ architecture is found to be better on the basis of MSE, MAE, RMSE, DA and AIC. Evaluating the performance of neural network using unseen testing data set of 100 observations, the neural network architecture consisting of 12 input nodes and 8 hidden layers ($NN_{12\times8}$) seems to be performing better on all grounds (table 8). The values of MSE, MAE and RMSE for best performing network in case of training, validation and testing are 0.0032, 0.0012 and 0.0013; 0.0417, 0.0271 and 0.0295; and 0.0562, 0.0342 and 0.0363 respectively. The correlation coefficients between actual and predicted returns are found to be significant in all networks using testing data set. The values of correlation coefficient and DA for best performing network in case of training, validation and testing are 0.5080, 0.4241 and 0.2779; and 74.32%, 48.48% and 47.47% respectively (table 8).

From the results shown in the table 2 and 6-8, it can be said that to a large extent stock market returns are predictable using AR and MLANN models. Table 9 shows that predictive power of artificial neural network is better than AR model as indicated by highlighted figures of MSE, RMSE and MAE. The MSE, RMSE and MAE are less for Neural Network compared to AR modeling. For instance, the MSE, RMSE and MAE in case 1 for AR model is 0.0031, 0.0553 and 0.0400 while it is 0.0028, 0.0527 ad 0.0388 for ANN respectively which are less in comparison to AR values. Similar difference exists in case 2 and 3 (table 9). Further, MSE and RMSE decreases as the number of observations in training set increases. This is equally applicable to both linear (AR) and non-linear (ANN) modeling.

Table 2
Resuts for AR Model

Dependent Variable: R

	AR-1500		*AR-1800*		*AR-1900*		*AR-2010*	
	Coeff	*t-Stat*	*Coeff*	*t-Stat*	*Coeff*	*t-Stat*	*Coeff*	*t-Stat*
C	0.5	255.5	0.501	288.9	0.501	301.3	0.501	316.5
AR(1)	0.071	2.753	0.07	2.971	0.071	3.105	0.073	3.263
AR(2)	-0.02	-0.69	-0.04	-1.68	-0.04	-1.68	-0.04	-1.78
AR(3)	0.016	0.63	0.029	1.231	0.03	1.295	0.029	1.278
AR(4)	0.04	1.555	0.054	2.291	0.057	2.466	0.056	2.487
AR(5)	-0.03	-1.18	-0.03	-1.36	-0.03	-1.41	-0.03	-1.32
AR(6)	-0.06	-2.2	-0.06	-2.55	-0.06	-2.67	-0.06	-2.86
AR(7)	0.021	0.81	0.019	0.809	0.02	0.859	0.021	0.926
AR(8)	0.024	0.928	0.009	0.36	0.007	0.29	0.008	0.345
AR(9)	0.07	2.686	0.066	2.783	0.066	2.888	0.064	2.871
R-squared	0.018	0.019	0.02	0.02				
Adjusted R-squared	0.012	0.015	0.015	0.016				
F-statistic	2.932	3.929	4.275	4.542				
Prob(F-statistic)	0.002	0	0	0				
Durbin-Watson stat	2	2.002	-2.663	-2.7				
Akaike info criterion	-2.617	-2.626	2.002	2.002				

Table 3
Q-Statistics for Autocorrelation

Lag	*Q-Stat(1500)*	*Q-Stat(1800)*	*Q-Stat(1900)*	*Q-Stat(2010)*
1	0.0038	0.0017	0.0016	0.0019
2	0.0170	0.0028	0.0034	0.0033
3	0.0556	0.0054	0.0063	0.0054
4	0.0563	0.0197	0.0220	0.0217
5	0.0868	0.0319	0.0363	0.0342
6	0.1061	0.0321	0.0365	0.0347
7	0.7383	0.0353	0.0398	0.0380
8	1.8403	0.0602	0.0677	0.0629
9	9.1844	0.0607	0.0699	0.0669
10	9.1909	0.3412	0.3310	0.4026
11	10.514	0.6890	0.8390	0.8653
12	10.580	1.0269	1.2325	1.1584
13	14.200	3.6797	4.0774	4.0779
14	16.101	6.6498	6.7728	6.6259
15	19.488	9.6268	10.262	10.044
16	19.759	9.7871	10.453	10.243
17	20.670	10.338	11.205	11.125
18	20.919	10.809	11.606	11.461
19	23.666	11.748	12.491	12.404
20	32.435	16.407	17.627	17.441
21	33.267	16.970	18.406	18.305
22	33.268	16.970	18.422	18.337
23	34.599	19.049	21.048	21.146
24	34.606	19.112	21.120	21.217
25	35.248	19.855	22.115	22.284

Table 4
Forecast by AR Model

Input data for estimation	1500	1800	1900
Forecasted observation	510	210	110
MSE	0.0031	0.0014	0.0014
RMSE	0.0553	0.0372	0.0376
MAE	0.0400	0.0300	0.0306

The empirical results for India do not support the hypothesis that financial liberalization has lead to increased efficiency and reduced the prediction possibility in stock prices. Grabel (1995) suggested that improved legal and regulatory environment and institutional arrangements basic to reform process would contribute to restrain excessive speculation and a decline in price volatility by aligning asset prices closer to fundamentals. But apparently the reverse is happening and the possible reasons are discussed in the next section.

Table 5
BDS Statistics
Residuals from the AR to Return

	Dimension (m)	*BDS Statistic*	*Std. Error*	*z-Statistic*	*Prob.*
			ε		
			0.5s		
R	2	0.008110	0.000818	9.915731	0.0000
	3	0.007583	0.000585	12.95417	0.0000
	4	0.004737	0.000314	15.06579	0.0000
	5	0.002571	0.000148	17.37970	0.0000
	6	0.001300	6.45E-05	20.16817	0.0000
			σ		
R	2	0.019490	0.001798	10.84211	0.0000
	3	0.031422	0.002332	13.47154	0.0000
	4	0.034404	0.002269	15.16193	0.0000
	5	0.032290	0.001933	16.70729	0.0000
	6	0.028275	0.001523	18.56068	0.0000
			1.5σ		
R	2	0.020672	0.001746	11.83655	0.0000
	3	0.041857	0.002964	14.12417	0.0000
	4	0.058663	0.003767	15.57253	0.0000
	5	0.069376	0.004191	16.55453	0.0000
	6	0.076105	0.004313	17.64432	0.0000
			2σ		
R	2	0.014543	0.001213	11.99198	0.0000
	3	0.032784	0.002351	13.94469	0.0000
	4	0.051995	0.003413	15.23590	0.0000
	5	0.068875	0.004334	15.89040	0.0000
	6	0.083929	0.005093	16.48084	0.0000

Notes: m-embedding dimension; ε-distance between points, measured in terms of number of standard deviations of the raw data; σ-standard deviation.
All statistics are significant at the 5 per cent level.

Table 6
ANN Results

	Training	*Validation*	*Testing*
Inputs→	13	5	7
Neurons→	12	8	12
MSE	0.0048	0.0021	0.0028
MAE	0.0526	0.0346	0.0388
RMSE	0.0690	0.0462	0.0527
MAD	0.0424	0.0261	0.0309
Corr	0.3273	0.1913	0.3147
P-Val	0.0000	0.0000	0.0000
DA	73.73	58.18	51.70
AIC	-5321	-3064	-2930

Table 7
ANN Results

	Training	*Validation*	*Testing*
Inputs→	12	7	15
Neurons→	16	3	12
MSE	0.0036	0.0039	0.0013
MAE	0.0449	0.0439	0.0293
RMSE	0.0601	0.0627	0.0367
MAD	0.0346	0.0319	0.0273
Corr	0.3802	0.4113	0.2611
P-Val	0.0000	0.0000	0.0011
DA	73.55%	54.27%	57.29%
AIC	-8975	-1094	-1292

Table 8
ANN Results

	Training	*Validation*	*Testing*
Inputs→	13	9	12
Neurons→	16	8	8
MSE	0.0032	0.0012	0.0013
MAE	0.0417	0.0271	0.0295
RMSE	0.0562	0.0342	0.0363
MAD	0.0329	0.0239	0.0284
Corr	0.5080	0.4241	0.2779
P-Val	0	0.0001	0.0051
DA	74.32%	48.48%	47.47%
AIC	-10337	-657	-639

Table 9
Comparative Predictive Performance

Input data for estimation	1500	1800	1900
Forecasted observation	500	200	100
	Auto Regression (AR) Model		
MSE	0.0031	0.0014	0.0014
RMSE	0.0553	0.0372	0.0376
MAE	0.0400	0.0300	0.0306
	Artificial Neural Network		
MSE	0.0028	0.0013	0.0013
RMSE	0.0527	0.0367	0.0363
MAE	0.0388	0.0293	0.0295

CONCLUDING REMARKS

The empirical results for India indicate the presence of inefficiency and predictability in stock prices. Autoregressive Models and Artificial Neural Network are used to predict the daily BSE Sensex returns and test for efficient market hypotheses. It is revealed in the study that AR model are capable to detect linear dependencies while nonlinearties are not detected as shown by BDS test. ANN is found to outperform AR predictions. It is observed from obtained result that MSE, RMSE and MAE decrease as the number of observations in training set increases. These results are equally applicable to both AR and MLANN modeling. Efficient market hypotheses are not supported by the data of BSE stock indices as indicated by AR and MLANN model. Further, it can be said that to a large extent stock market returns are predictable.

These results seems to suggest that more steps on the part of government, RBI and SEBI are required to bring more transparency in the equity markets. Over the years transactions costs have come down, trades are guaranteed and screen based trading has done away with settlement problems. The role of intermediaries has reduced due to online trading of equity shares through ICICI bank and HDFC bank's demat accounts among others. However, market efficiency is linked to information which is costly (both in terms of money and time) and monitoring and enforcing regulations are not costless, nor perfect. The results suggest that certain anomalies such as insider trading, price rigging by management, circular trading, dissemination of information about FIIs trades among others still exist which may be making the equity markets inefficient and predictable.

There is a link between market inefficiencies and trading profits. Market intermediaries are closest to markets, are able to respond fastest to market inefficiencies, and hence are best able to obtain trading profits from inefficiencies. The rents that flow from faulty market structures give intermediaries the sharpest incentives to engage in political actions, which increase transactions costs, block reforms to market institutions, and maximize market inefficiencies. For instance, BSE brokers earned enormous trading profits as a direct consequence of the inefficiencies of the BSE floor. Intermediaries in equity markets have unique incentives to block institutional change which eliminates their special status and ends these trading profits. In view of emergence of equity market as the barometer of economic performance of the economy, there is a need of committed effort on the part of government, RBI and SEBI to bring transparency and immediate dissemination of information would help in minimizing inefficiency and reduce predictability.

Notes

1. The forecasts can be either static or dynamic; static forecasts use actual values of lagged dependent variables, where these are required, whereas dynamic forecasts use the previously forecast values of these variables. Since the errors made in dynamic forecasting for periods early in the forecasting horizon contaminate forecasts for later periods as well, forecast errors in dynamic forecasts are expected to be greater than those in static forecasts.
2. The results for all network are not given in the paper for saving the space, because there are 540 networks. However, the results for all networks are available with authors and can be provided on demand.

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