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Markov Process Model Forecasting of Quarterly Accounting Earnings Per Share

KEYWORDS: earnings per share, forecasting, Markov process model

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ABSTRACT *Earnings per share (EPS) is one of the predominant factors that evaluate a company's financial performance either in the short run or in the long run thereby indicating the prospects of a company for investors to make wise decisions. Needless to say, quarterly accounting earnings in prospective analysis tends to be an essential task and seasonality evident to be an important phenomenon in data behavior. The present study explores the capability of predicting the EPS by expounding on the related properties of Markov process model which is a useful complement for an existing technical analysis. A data sample of HCL infosystem trading on the Bombay stock exchange (BSE) is employed here and the forecasting performances are calculated. The results demonstrate that the Markov process model is competitive and a competent one in prospective analysis.*

1. INTRODUCTION

EPS is one of the predominant factors that evaluate a company's financial performance either in the short run or in the long run thereby indicating the prospects of a company for investors to make wise decisions. EPS reflected the good or bad position of the company and its increase is not only reflected in the market price in the stock exchange but also in the profit earnings ratio, dividend cover, dividend yield and earnings yield [1]. Earnings analysis, especially earning forecasting, plays a critical role in analytical and empirical literature in finance and accounting [2]. EPS is the net income available to common shareholders divided by the weighted average number of common shares outstanding. Many investors select stocks on the basis of company's earnings forecasts which are often used to determine earnings expectation when investigating firm valuation, cost of capital and the relationships between earnings and stock prices.

Although the concept of EPS is simple and straightforward, EPS forecasting is a very challenging task. Forecasting EPS has long been an interest to investors, financial decision makers, researchers and practitioners. Investors use these forecasts as a basis to configure their investment portfolios, market risks and top management use for a host of important decisions including capital investment and operational budgeting. Accurate forecasts therefore are essential for both optimum portfolio management in capital markets and optimum resource allocation within a firm [3] [4].

The present study explores the capability of predicting the EPS by expounding on the related properties of Markov process model which is a useful complement for an existing technical analysis. A Markov chain is a special kind of stochastic process where the outcome of an experiment depends only on the outcome of the previous experiment. In other words, the next state of the system depends only on the current state and not on the previous states. Stochastic processes are of interest for describing the behavior of a system evolving over a period of time.

The purpose of this work is to review and classify the Markov process models to forecast the EPS. The results are presented in four models. The first and second lists the basic model with only two states namely growth and decrease. The third model lists the extended model of Y_t with eight states distinguishing different levels of growth and decrease. The final model lists the extended model of K_t with eight states. The work focuses on the application of Markov process model to predict the EPS. This model may be applied to diverse markets to forecast the stock market EPS.

The rest of the paper is organized as follows. Section 2 describes related studies. Section 3 explains the basics of Markov process model. The Markov prediction model is presented in section 4.This section provide various state model and their transition probability matrices. Finally the conclusions of the study are summarized in section 5.

2. RELATED WORKS

In [5], the study compared the ability of neural network (NN) model and linear time series model to forecast quarterly accounting earnings for a large sample of corporations trading on the New York stock exchange. The work used rolling samples of 40 quarters in length each for NN approach to generate one quarter ahead earnings forecasts. Each rolling sample is broken down into 36 adjacent point 4-tuples of the form $(x_{t-3}, x_{t-2}, x_{t-1}, x_t)$ as inputs and 36 corresponding outputs of the form x_{t+1} to facilitate learning by NN. Thus the first rolling sample consists of 36 inputs represented by the 4-tuples (x_1, x_2, x_3, x_4), (x_2, x_3, x_4, x_5), …. $(x_{36}, x_{37}, x_{38}, x_{39})$ and their corresponding outputs $x_5, x_6 \ldots x_{40}$. The input buffer of NN receives data from the 4-tuples of the form $(x_{t-3}, x_{t-2}, x_{t-1}, x_t)$. The hidden layer is used to capture the input features. The output layer generates the single earnings number x_{t+1}. The resulting forecast errors are shown to be significantly smaller than those generated by parsimonious Brown-Rozeff and Griffin-Watts (Foster) linear series model.

The work has combined the advantages of both sliding window multiple regression (SWMR) and multi-objective genetic algorithms (MOGA) to maximize the forecasting accuracy with minimal number of financial ratios such as book value per share, operating income growth rate, total growth rare [6]. The genetic algorithm (GA) generates the next-generation population from the parent population according to the finesses of chromosomes. The sum of squared errors of each individual in the newer population will be evaluated by the SWMR mechanisms. The forecasting accuracy of the proposed mechanism is better than that of moving average model, simple auto regression model, simple exponential model and stepwise model.

The paper proposed hidden Markov models (HMM) approach to predict time series behavior from past data sets [7]. The author has used only one HMM that is trained on the past data set. Then the trained HMM is used to search for

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the variable of interest behavioral data pattern from the past data set. Finally the work has interpolated these two data sets with appropriate neighboring price elements and forecasts tomorrow's stock price.

In [8] the study has evaluated the ability among an Auto regressive integrated moving average (ARIMA) model, transfer function (TF) model, NN model and GA model to forecast the EPS. The deviation between an actual and forecasted quarterly EPS value, the direction changes from quarter to quarter between an actual and forecasted quarterly EPS value were considered for evaluating the forecasting accuracy. Empirical results have shown that the TF model outperforms the ARIMA model. Therefore, the time lags setting of the TF model is adopted in the other two models: GA and ANN. The results also reveals that the GA model has the best forecasting accuracy under both basic EPS (BEPS) and diluted EPS (DEPS), while the ANN model has been shown to have the worst forecasting accuracy under both BEPS and DEPS.

The research study integrated financial statement related indicators to forecast the EPS [9]. The author has integrated an ANFIS with the decision tree which is the pre-process for enhancing predicting ability. This study consists of i) feature selection to reduce attributes, and the attributes are discretized by decision trees then encoding the dicretization value ii) take fuzzy inference system (FIS) to fuzzify the encoding value, and use adaptive network to tune optimal parameters. iii) employ an integrated ANFIS model to predict EPS. The proposed method outperformed the conventional data mining models in accuracy.

The author has investigated the efficiency and ability of applying gray group model (GM) to forecast the EPS [10]. This GM consists of data preparation, grey group model and validation stages. Given the non-negative series $y^{(0)} = \{x^{(0)}(i), i = 1, 2 \ldots N\}$. A GM (1,1) is the solution of the pseudo difference equation formed as $\frac{dy^{(1)}}{dt} + az^{(1)} = b$, where $z^{(1)}(i) = \frac{1}{2}(y^{(1)}(i) + y^{(1)}(i-1))$ for $2 \leq i \leq N$ and $y^{(1)}$ i is accumulated generating sequence. The advantage of this model includes such as it is easy to calculate, needs only few observations than statistical method and liberates the users from the sample data assumptions from statistical analysis such as identically independent distribution. Further the in-sample and post-sample forecast performances also showed that the GM with proper amount of observations is a competitive method for the non-stationary seasonal time series analysis, forecast and control. But identifying the appropriate mean factors in GM and appropriate number of observations for model building in different application cases were difficult.

The work has compared the accuracy of NN with BP and NN with GA in forecasting EPS based upon fundamental accounting variables [11]. Each input layer node of NN had a weighted connection to each hidden node in the input layer. Each hidden layer node had a weighted connection to each output layer node. GA had assumed a single hidden node, evolved one thousand generations, added a second node, and has evolved another N generations. This process has continued until the addition of 3 consecutive nodes failed to provide a new set of parameters estimates with better fit characteristics than all proceeding solution. The results showed that without using fundamental variables, the forecasting accuracy of the NN model estimated with GA is higher than that of the NN model with BP. When using fundamental variables, the forecasting accuracy of the NN model estimated with GA is improved overall models. The work further contributes by revealing that the NN model estimated with GA has greater forecasting accuracy then the NN model estimated with BP. In addition it has confirmed that the addition of fundamental accounting variables in the NN model improves the forecasting accuracy in predicting EPS.

In [12], the author proposed a fusion forecasting model that incorporates an autoregressive model (AR) into an ANFIS model. The proposed model consists of data preprocessing, rule generation and performance evaluation. The data preprocessing consisted of collecting EPS data and testing the lag period of EPS by least square method. Rule generation consisted of generating FIS and training parameters of FIS from training data sets. The performance evaluation of the proposed model is tested with minimal root mean squared error. Then the best model based on the minimal RMSE value is selected and the performances of different models are compared. The proposed AR into an ANFIS model performance is superior than linear regression, AR (1), multilayer perceptron and radial basis function in 5 out of 8 testing data sets.

This study has investigated the NN with error back propagation (EBP) and NN with a GA model to forecast the EPS [13]. It has considered the relation of real value of inventory to number of common shares, relation of commercial received accounts to the number of common shares, relation of non-commercial received accounts to the common shares, relation of capital expenditure, relation of gross earnings to number of common shares, effective tax rate, labor force productivity logarithm as independent variables. Once the data is normalized it will be fed into NN which consists of 8 input layer, 24 hidden layer and 1 output layer. The findings reveal that the error rate whether with an EBP algorithm or a GA, is low and therefore an ANN is definitely useful for forecasting EPS. However from the comparison between the two training algorithms, it was observed that the ANN is more accurate and less error than the ANN with a GA.

3. MARKOV PROCESS MODEL

The present study aims at trying to predict the stock market EPS using Markov chain model. Markov theory is seen to be relevant to the analysis of stock prices by making probabilistic statements about future stock price levels. A Markov chain is a special kind of stochastic process where the outcome of an experiment depends only on the outcome of the previous experiment. In other words the next state of the system depends only on the current state and not on the previous states. Stochastic processes are of interest for describing the behavior of a system evolving over period of time.

Stochastic process in the form of discrete sequence of random variables $\{x_n\}$, n =1, 2…. is said to have Markov property if $P(X_{n+1}=i_{n+1} / x_n=i_n, x_{n-1}=i_{n-1} \ldots\ldots x_2=i_2, x_i=i_1) = P(X_{n+1}=i_{n+1}/x_n=i_n)$ holds for any finite n, where particular realizations x_n belong to discrete state space $S = \{s_i\}$, i=1,2…k. The process of moving one state of the system to another with the associated probabilities of each transition is known as a chain. The transition probabilities from m x m transitional probability matrix T, where

$$T = [P_{ij}] = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1m} \\ P_{21} & P_{22} & \cdots & P_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ P_{m1} & P_{m2} & \cdots & P_{mm} \end{bmatrix}$$

with the following properties

(i) Pij > 0 for all i and j
(ii) $\sum_{j=1}^{n} P_{ij} = 1$ for all i and j
(iii) the diagonal element represents transition from one state to same state

Each row of T is the probability distribution relating to a transition from state i to state j. A chain is said to have a steady state distribution if there exists a vector P such that given transition matrix T, we have ∏T=∏. This steady state vector can be viewed as the distribution of random variable in the long run. In our study, we aim at modeling of EPS value and its trend development by Markov chain. Also we discuss trend prediction using time series analysis.

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4. MARKOV PREDICTION MODEL

We have analyzed the model construction and forecasting process using Markov chain by imposing several requirements on the data. The research framework and models with specific description of the steps are characterized as follows

(i) Input selection
(ii) Data preprocessing
(iii) Classification of states
(iv) Construction of state process and state probability
(v) Construction of state transition probability matrix
(vi) Forecasting the state probability of EPS

(i) Input selection

EPS values of the HCL infosystem were gathered from BSE for the period starting from March 2000 to December 2011 consisting of 48 quarterly EPS data.

(ii) Data preprocessing

To facilitate the learning process of the prediction model and to increase the accuracy of the prediction the data has to be processed. Input data were preprocessed to analyze and forecast the EPS.

(iii) Classification of states

EPS values are divided into growth, decrease, sub categories of growth and sub categories of decrease.

Model 1

This basic model classifies the states based on whether the chain index of quarterly EPS Y_t is less than or greater than or equal to 1. Then the states are:

State 1: The chain index of quarterly EPS is less than 1 ($Y_t < 1$)

State 2: The chain index of quarterly EPS is greater than or equal to 1 ($Y_t \geq 1$)

Model 2

Here the classifications of the states are based on the input values as greater than or lesser than the previous quarter, thus allowing two state classification.

State 1: Current EPS is greater than the previous EPS.

State 2: Current EPS is lesser than the previous EPS.

These two models provide general information and have limited prospects of only two possible transition states of growth and decrease.

Model 3

Different levels of growth and decrease of Y_t are distinguished by partitioning into 4 transitional states each namely $\{D_4, D_3, D_2, D_1, G_1, G_2, G_3, G_4\}$. Then the eight states are:

State 1: $Y_t < 0.7$ (D_4)

State 2: $0.7 \leq Y_t < 0.8$ (D_3)

State 3: $0.8 \leq Y_t < 0.9$ (D_2)

State 4: $0.9 \leq Y_t < 1.0$ (D_1)

State 5: $1 \leq Y_t < 1.1$ (G_1)

State 6: $1.1 \leq Y_t < 1.2$ (G_2)

State 7: $1.2 \leq Y_t < 1.3$ (G_3)

State 8: $Y_t \geq 1.3$ (G_4)

Model 4

Similar to the previously described model, growth and decrease of K_t are partitioned by subcategorizing the 4 transition states each namely $\{D_4, D_3, D_2, D_1, G_1, G_2, G_3, G_4\}$. Then the eight transition states are:

State 1: $K_t < 0.7$ (D_4)

State 2: $0.7 \leq K_t < 0.8$ (D_3)

State 3: $0.8 \leq K_t < 0.9$ (D_2)

State 4: $0.9 \leq K_t < 1.0$ (D_1)

State 5: $1.0 \leq K_t < 1.1$ (G_1)

State 6: $1.1 \leq K_t < 1.2$ (G_2)

State 7: $1.3 \leq K_t < 1.3$ (G_3)

State 8: $K_t \geq 1.3$ (G_4)

Model 3 and Model 4 are better classified and are more precise. Prediction accuracy tends to be more reliable in these models. Desirable exploration aims at further betterment. Sophisticated and smarter way of such explorations leads to a different dimension of approaches and perspectives.

(vi) Construction of state process & state probability

We considered each quarterly EPS as discrete time units and divided into two basic states namely growth and decrease. Then the state space is $E(x_1, x_2)$ and state probability is the possible size of emergence of a variety of state. State vector is denoted by $\eta_{(1)} = (P_1, P_2 \ldots P_n)$ where $i = 1, 2\ldots n$, P_j is the probability of x_j, $j = 1, 2\ldots n$.

For model 1 the probability of each state are as follows: $P_1 = 22/47$ and $P_2 = 25/47$ and state vector $\eta_{(0)} = (0.4681, 0.5319)$ is called initial state vector.

For model 2, $P_1 = 23/48$, $P_2 = 25/48$ and $\eta_{(0)} = (0.4792, 0.5208)$.

(v) Construction of state transition probability matrix

This section analyses the above information by using Markov chain and forecasts the EPS for the subsequent quarter.

Processing Y_t of model 1 provides the transition probability matrix P_1 given by

$$P_1 = \begin{matrix} & s_1 & s_2 \\ s_1 & 0.318 & 0.682 \\ s_2 & 0.583 & 0.417 \end{matrix}$$

We found that

$$P_1^8 = \begin{pmatrix} 0.4609 & 0.5391 \\ 0.4609 & 0.5391 \end{pmatrix}$$

indicating the steady state probability vector $\pi_1 = (0.4609, 0.5391)$.

Processing model 2 yields the transition matrix P_2 given by

$$P_2 = \begin{matrix} & s_1 & s_2 \\ s_1 & 0.318 & 0.682 \\ s_2 & 0.6 & 0.4 \end{matrix}$$

We found that

$$P_2^8 = \begin{pmatrix} 0.4680 & 0.5320 \\ 0.4680 & 0.5320 \end{pmatrix}$$

So that the steady state vector $\pi_2 = (0.4680, 0.5320)$.

Model 1 and Model 2 has roughly the same steady state vector, indicating that over a long period both model have same probability distribution. Also these models indicate that given a day is in either state there is a greater chance of transiting to a state of decrease than a state of growth. The steady state vector π_1 and π_2 showed that there is a greater probability of a day being a day of decrease than a day of growth.

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It is very interesting to note that the chain index of EPS and EPS alone are being used model 1 and model 2 respectively and the results obtained both the models gives almost same state probability of future.

Processing model 3 provides both transition probability matrix P_3 and conditional probabilities of decrease and growth depending upon states D_i and G_i, i = 1, 2, 3, 4 respectively which constitutes the columns of matrix Q_1 listed as

$$P_3 = \begin{bmatrix} 0 & 0.143 & 0.143 & 0 & 0.143 & 0.143 & 0 & 0.429 \\ 0.166 & 0 & 0.166 & 0.166 & 0.166 & 0.166 & 0 & 0.166 \\ 0.166 & 0 & 0.166 & 0 & 0 & 0.330 & 0.166 & 0.166 \\ 0.200 & 0.200 & 0 & 0.2 & 0.200 & 0 & 0 & 0.200 \\ 0.200 & 0.200 & 0.200 & 0.2 & 0 & 0 & 0.200 & 0 \\ 0 & 0.143 & 0.286 & 0.286 & 0.286 & 0 & 0 & 0 \\ 0.333 & 0.333 & 0 & 0 & 0 & 0.333 & 0 & 0 \\ 0.429 & 0.143 & 0 & 0 & 0 & 0.149 & 0.149 & 0.149 \end{bmatrix}$$

$$Q_1 = \begin{bmatrix} 0.286 & 0.714 \\ 0.498 & 0.498 \\ 0.334 & 0.666 \\ 0.6 & 0.4 \\ 0.8 & 0.2 \\ 0.714 & 0.286 \\ 0.667 & 0.333 \\ 0.572 & 0.428 \end{bmatrix}$$

Here we conclude that state G_1 provides 0.8 probability of decrease and state D_4 provides 0.714 probability of growth.

Since state D_4 gives the greatest probability of increase we start with $p(D_4) = 1$. The probabilities of the various states are summarized in table 1. The maximal conditional probabilities are located at the state G_4.

TABLE - 1
STATE PROBABILITY OF MODEL 3

$P(D_4)$	$P(D_3)$	$P(D_2)$	$P(D_1)$	$P(G_1)$	$P(G_2)$	$P(G_3)$	$P(G_4)$
0	0.143	0.143	0	0.143	0.143	0	0.429
0.260	0.110	0.117	0.093	0.065	0.132	0.114	0.109
0.154	0.141	0.126	0.088	0.118	0.148	0.478	0.183
0.178	0.125	0.131	0.105	0.105	0.129	0.069	0.154

Since state G_1 gives the greatest probability of decrease we start with $p(G_1) = 1$ and the maximal conditional probabilities are located in D_4.

Similarly we processed model 4, which is based on K_t provides both transition matrix P_4 and conditional probabilities Q_2.

$$Q_2 = \begin{bmatrix} 0.200 & 0.800 \\ 0.499 & 0.499 \\ 0.500 & 0.500 \\ 0.750 & 0.250 \\ 0.667 & 0.333 \\ 0.666 & 0.334 \\ 0.666 & 0.334 \\ 0.700 & 0.300 \end{bmatrix}$$

When searching the maximal values in columns of Q_2 state D_1 provides 75% of decrease and state D_4 provides 80% of growth. Another interesting point to here is the states G_1, G_2 and G_3 having the same growth rate (66.6%) and decrease rate (33.4%).

When starting with $P(D_4) = 1$, the maximal conditional probabilities are located at state G_4 and with $P(D_1) = 1$, it is located at D_4.The probabilities of the various states of this model are summarized in table 2.

TABLE - 2
STATE PROBABILITY OF MODEL 4

$P(D_4)$	$P(D_3)$	$P(D_2)$	$P(D_1)$	$P(G_1)$	$P(G_2)$	$P(G_3)$	$P(G_4)$
0.200	0	0	0	0.100	0.200	0.100	0.400
0.193	0.153	0.140	0.100	0.020	0.073	0.087	0.233
0.261	0.149	0.070	0.061	0.070	0.111	0.038	0.237
0.247	0.124	0.078	0.071	0.066	0.113	0.068	0.231

(vi) Forecasting the state probability of EPS

In Markov process, we know that $\eta_{(i+1)} = \eta_{(i)} * P$ where $\eta_{(i)}$ denotes the state probability in different periods and P is state transition probability matrix. Since initial vector for model 1 is (0, 1) and we have

$$\varsigma_1 = (0,1)\begin{pmatrix} 0.318 & 0.682 \\ 0.583 & 0.417 \end{pmatrix}$$
$$= (0.583, 0.417)$$

The initial vector for model 2 is (0, 1) and we have

$$\varsigma_1 = (0,1)\begin{pmatrix} 0.318 & 0.682 \\ 0.6 & 0.4 \end{pmatrix}$$
$$= (0.6, 0.4)$$

Similarly we calculate the subsequent quarter and the results are summarized in Table 3.

TABLE - 3
STATE PROBABILITY OF FUTURE EPS

Quarter	Model 1		Model 2	
March 13	0.4615	0.5385	0.4689	0.5311
June 13	0.4607	0.5393	0.4678	0.5322
Sep' 13	0.4609	0.5391	0.4681	0.5319

5. CONCLUSIONS

It can be concluded that EPS is a classical tool relied upon by the investment analysts to measure the performance of business. In this paper we proposed and discussed the results on three models with time independent transition probability matrices to analyze and predict the EPS data of HCL infosystem. Markov process model establishes the fact of how the entire market was useful in gauging the behavior of portfolio of stocks. This model inheres easy to calculate and used only few observations than statistical model when model building. Markov trend prediction of EPS in a particular quarter is forecasted thereby paving a way for future work which may enhance problem oriented filtering procedures of trade sequence for better prospects. Furthermore state space of transition probability matrices may classify using computationally intelligent classification algorithm for better results.

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