THE LONG-RUN PROSPECT OF STOCKS IN THE NIGERIAN CAPITAL MARKET: A MARKOVIAN ANALYSIS

Eseoghene Joseph Idolor
Department of Banking and Finance, University of Benin, Benin City, Nigeria
E-mail: greatidolor@yahoo.com, eseoghene.idolor@uniben.edu

Abstract
This study presents a method of Markovian analysis of the long-run prospects of security prices in Nigeria. It examines five securities randomly selected from the banking sector of the Nigerian Stock Exchange for the period spanning January 4th 2005, to June 30th 2008; and defines a set of three states (rise, drop and stable) for the process in terms of a Markovian framework. The findings suggest that price levels are likely to remain relatively stable in the long run irrespective of the current down turn of prices and global economic meltdown. It must however be noted that as is the case with every long range projection, the possible future occurrence is fraught with many probabilities (including chance events) and only time can prove whether the projections are valid or not. Nevertheless the technique provided here adds to the very rich, and often conflicting literature on stock price prediction or behaviour. It is therefore recommended that the techniquebe added to the very rich store of methods adopted by technicians (technical analyst) in evaluating and arriving at long range projections on the future prospect of stocks.

Keywords: Markov chains, fundamental analysis, technical analysis, stock price transition

Introduction

Predicting the long-run prospect of stock prices has always been a difficult and complex problem. Though many methods may exist, there still remains many grey area's where controversies exist and for which new insights and methods will have to be developed to better capture the causes of price changes, and how best to predict its behaviour.

Naturally, prediction of stock prices is usually characterized by a great degree of data intensity, uncertainty and hidden relationships. Many factors interact together in a disproportionate manner in influencing the prices of stocks which are traded on the floor of stock exchanges worldwide. These includes, but are not limited to political events, general economic conditions and traders expectations. Therefore, determining the long-run prospects of securities has proved to be quite a difficult challenge; as increasingly academic investigations have tended to agree with the notion that stock price movements are random and as such behaves in a dynamic and unpredictable manner (see, for example, Fielitz and Bhargava, 1973; Fielitz, 1969; Turner, Startz and Nelson, 1989; Hamilton, 1989; Obodos, 2005; and Idolor, 2009).

Stock price prediction (for the long term) is basically an activity which is performed by many categories of capital market operators and participants who are very much interested in investing their funds in those stocks with good prospects and thus reaping capital gains in the future (Frear, 1988). It is also worthy of note that the techniques and methods adopted over the years have been very dynamic and in line with the ever changing financial environment.

Markov theory is seen to be relevant to the analysis of stock prices in two ways: As a useful tool for making probabilistic statements about future stock price levels and secondly as an extension of the random walk hypothesis. In this role, it constitutes an alternative to the more traditional regression forecasting techniques to which it is in some unique way superior in the analysis of stock price behaviour. Markov theory is concerned with the transition of a system from one state to another. in the case of a sequence of observations on stock prices, the states of the system may be thought of as the set of all possible prices that might be observed for a given stock. Since the number of states so defined is virtually infinite, it is sometimes convenient to group prices into price ranges, or price classes. That security prices may be interpreted as a Markov process means certain theorems relating to the theory of Markov processes may be brought to bear, enabling us to answer certain questions concerning the future price level of a given stock (Ryan, 1973). In this study, the model considered is that of a first-order Markov Chain. Also, the particular Markov Chain studied here has a finite number of states and a finite number of points at which observations are made. In the analysis, we made use of standard methods, developed by Anderson and Goodman (1957), which was adopted and applied in Fielitz (1969 and 1971), Fielitz and Bhargava (1973), Obodos (2005), and Idolor (2009).

Markov processes

The occurrence of a future state in a Markov process depends on the immediately preceding state and only on it (Taha, 2001).

If $t_0 < t_1 < \ldots t_n$ ($n = 0, 1, 2, \ldots$) represents points in time, the family of random variables $\{\xi_{tn}\}$ is a Markov process if it possesses the following Markovian property:

$$P\ \{\xi_{tn} = X_n | \xi_{tn-1} = X_{n-1}, \ldots, \xi_{t0} = X_0\} =$$
$$P\ \{\xi_{tn} = X_n | \xi_{tn-1} = X_{n-1}\}$$

For all possible values of $\xi_{t0}, \xi_{t1}, \ldots, \xi_{tn}$.

The probability $P_{xn-1}, X_n = P\ \{\xi_{tn} = X_n | \xi_{tn-1} = X_{n-1}\}$ is called the transition probability. It represents the conditional probability of the system being in X_n at t_n, given it was in X_{n-1} at t_{n-1} (with X representing the states and t the time). This probability is also referred to as the one-step transition because it describes the system between t_{n-1} and t_n. An m-step transition probability is thus defined by

$$P_{xn}, X_{n+m} = P\ \{\xi_{tn+m} = X_{n+m} | \xi_{tn} = X_n\}$$

Markov Chains

Markov chains are a special class of mathematical technique which is often applicable to decision problems. Named after a Russian Mathematician who developed the method. It is a useful tool for examining and forecasting the frequency with which customers remain loyal to one brand or switch to others. For it is generally assumed that customers do not shift from one brand to another at random, but instead will choose to ‘buy brands in future that reflects their choices in the past. Other applications of Markov Chain analysis include models in manpower planning, models for assessing the behaviour of stock prices, models for estimating bad debts or models for credit management (Agbadudu, 1996).

A Markov chain is a series of states of a system that has the Markov property. At each time the system may have changed from the state it was in the moment before, or it may have stayed in the same state. This changes of state is called transitions. If a sequence of states has the Markov property, it means that every future state is conditionally independent of every prior state given the current state (Obodos, 2005).

Markov Chains is a sequence of events or experiments in which the probability of occurrence for an event depends upon the immediately preceding event. It is also referred to as first-order Markov Chain Process, first-order-Markov process or Markov Chain.

Applications of Markov Chains

A typical stock market observer is faced with the problem of predicting the future behaviour either of the market or of a particular stock. By utilizing Markov chain models, the behaviour both of a population of stocks, and of individual stocks over a period of time can be analysed and observed for the explicit purpose of learning how to predict future price behaviour wholly on the basis of past price information (Fielitz, 1969). There are two ways of looking at the problem. One can study the individual process Markov chain model, or one can consider the vector process Markov chain. The individual process Markov chain allows one to study the change behaviour of each individual stock while the vector process Markov chain considers not only the individual processes describing particular stocks, but also the process that characterizes the stock market as a whole. In the vector process Markov chain model, the processes for each component stock are themselves considered as Markov chains. Once the states are defined, an empirical representation for the vector process and each individual process can be considered by the formation of a series of matrices of transition observations.

Markov analysis is basically a probabilistic technique which does not provide a recommended decision. Instead, Markov analysis provides probabilistic information about a decision situation that can aid the decision marker in making a decision; as such it is more of a descriptive technique that results in probabilistic information (Taylor, 1996). Markov analysis is specifically applicable to systems that exhibit probabilistic movement from one state (or condition) to another, over time. For example, Markov analysis can be used to determine the probability that a machine will be running one day and broken down the next, or that a customer will change brands of products from one month to another-typically known as the brand switching problem. This is one area that it has found popular application; and is basically a marketing application that focuses on the loyalty of customers to a particular product brand, store, or supplier. Other applications are in the field of finance, where attempts have been made to predict stock returns, prices as well as to test the random walk hypothesis and other aspects of the efficient market hypothesis under a different set of assumptions than are traditionally needed. For example, the Markov tests do not require annual returns to be normally distributed although they do require the Markov Chain to be stationary. Markov chain stationarity is defined as constant transition probabilities over time. However, one cost of modeling returns with Markov chains is the information that is lost when continuous valued returns are divided into discrete states (Mcqueen and Thorley, 1991).

Niederhoffer and Osborne (1966) use Markov Chains to show some non-random behaviour in transaction to transaction ticker prices resulting from investors tendency to place buy and sell orders at integers (23), halfs (23½), quarters and odd eights in descending preferences. Dryden (1969) applies Markov Chains to U.K. (United Kingdom) stocks which, at the time, were quoted as rising, falling, or remaining unchanged. Fielitz (1969), Fielitz and Bhargava (1973) and Fielitz (1975) show that individual stocks tend to follow a first order, or higher order, Markov Chain for daily returns; however, the process is not stationary, neither are the chains homogenous. While Samuelson (1988) uses a first order Markov Chain to explore the implications of mean regressing equity returns.

A two-state Markov Chain is used by Turner, Startz, and Nelson (1989) to model changes in the variance of stock returns and Cecchetti, Lam and Mark (1990) show that if economic driving variables follow a Markov Chain process, then the negative serial correlation found in long horizons can be consistent with an equilibrium model of asset pricing. Markov Chains have also been used to model other asset markets, for example, Gregory and Sampson (1987), Hamilton (1989), and Engle and Hamilton (1990).

Mcqueen and Thorley (1991) used a Markov Chain model to test the random walk hypothesis of stock prices. Given a time series of returns, they defined a Markov Chain by letting one state represent high returns and the other to represent low returns. The random walk hypothesis restricted the transition probabilities of the Markov Chain to be equal irrespective of the prior years. The results showed that annual real returns exhibited significant non-random walk behaviour in the sense that low (high) returns tended to follow runs of high (low) returns for the period under consideration.

Research methodology

Research design

The longitudinal survey research design was used in this study. This is because we studied the stock price movement of our selected banks over a period of time. To this end data was collected about the same phenomenon at different points in time without any attempt on the part of the researcher to influence the data. The data obtained revealed changes in the variable (stock price) of interest over time.

Data gathering

As at January 2005, the population of Nigerian banks stood at eighty-nine (89). A simple random selection, by balloting, of five (5) banks listed on the Nigerian stock exchange was undertaken. The daily stock prices of the five (5) randomly selected banks over a three year period covering 4th January 2005 to 30th June 2008 served as the data source. The data gathered from the official website of The Nigerian Stock Exchange and Cashcraft Asset Management Limited showed the price movements of the randomly selected banks for the period under investigation. The only restriction made in selecting the stocks is that price data must have been available for the entire period covered, i.e., the bank must have been in existence and quoted on the Nigerian Stock Exchange since 4th January 2005. The banking sector of the Nigerian bourse was chosen because it represented the most vibrant and actively traded sector of the stock exchange.

Finally, for the period under study, all data utilized were secondary in nature and were derived from secondary sources. The five randomly selected banks that were used for this study are:

(1) Access Bank Plc
(2) Eco Bank Nigeria Plc
(3) First Bank of Nigeria Plc
(4) Intercontinental Bank Plc
(5) Union Bank of Nigeria Plc

Model of stock price transition

A model is a theoretical construct that represents processes through a set of variables and a set of logical and quantitative relationships between them. As in other fields, models are simplified frameworks designed to illuminate complex processes. The goal of the model is that the isolated and simplified relationship has some predictive power that can be tested using appropriate statistical tools. Ignoring the fact that the *ceteris paribus* assumption is being made is another big failure often made when a model is applied. At the minimum, an attempt must be made to look at the various factors that may be equal and take those into account (Abosede, 2008).

For the study a three state Markov Chain model aptly described as rise (r), drop (d) and stable (s); is used to show the three basic possible price movement of a stock. With this, we can derive the probability of the stock price rising, dropping or remaining stable; and on the basis of these probabilities attempt to predict the future price direction of a stock, with the sum of the probabilities equaling one. This three state system is set as the initial probability vector (U_o) which gives the probability of the system being in a particular state.

Furthermore, given the previous state (price) of a stock whether in a rise (r), drop (d) or stable (s) state; transition to a new state of rise, drop or stable is also possible. This we can have as a rise in price leading to another rise (rr), or drop (rd) or stable prices (rs). We can also have a drop leading to a rise (dr), or drop (dd) or stable prices (ds). Finally, we can have a stable price situation leading to a rise in prices (sr), drop (sd) or stable prices (ss). Markov Chains are often described by a directed graph, where the edges are labeled by the probabilities of moving from one state to the other. The directed graph for our model of stock price transition is thus shown in figure 1.

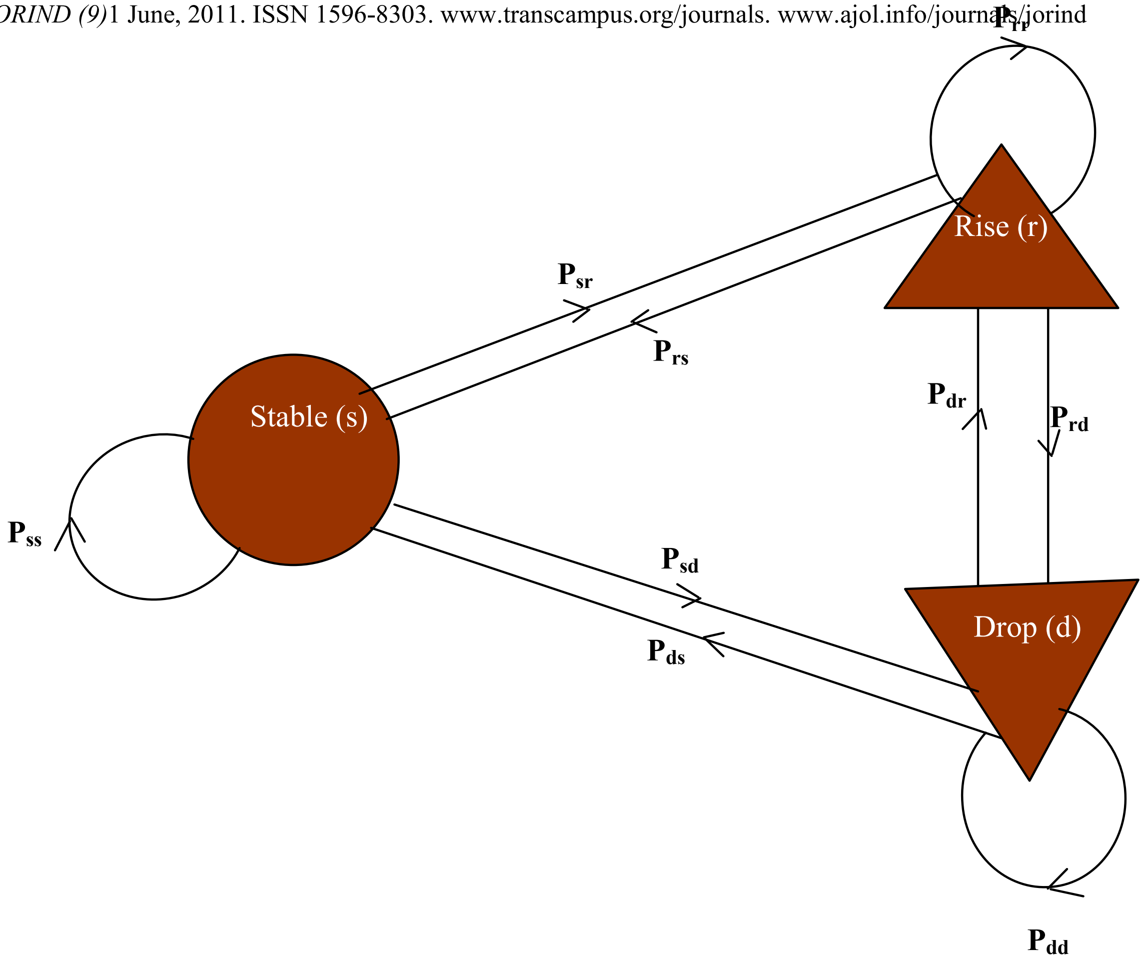

Figure 1: Diagram of Transition

From the three state system shown in figure 1, transition could occur from state x to state y or state z depicted as s (stable), r (rise) and d (drop). Therefore, for any transition, the probability of moving to the next state is given as P_i and the sum of probabilities must equal 1, depicted as follows:

$$\sum_{i=1}^{n} P_i = 1$$

If we assume that the system was previously in a particular state x, transition from the previous state x to a new state is possible provided the previous state is in a non-absorbing state. A state ij is called absorbing if it is impossible to leave that state. The state ij is thus absorbing if and only if $P_{ij} = 1$ and $P_{ij} = 0$ for $i \neq j$. Therefore, given an initial probability vector U_o, we can compute the probability of it being in the next state once we have derived the transition matrix. Therefore

$U_1 = U_0.P$ (Note that U_o and P are vectors)
$U_2 = U_1.P$
$U_3 = U_2.P$
$U_n = U_{n-1}.P$

The various probabilities for this occurrence can be put in a matrix P, which is called the transition matrix and shows the probability of the system moving from state to state. It gives the probability of transiting from rise to rise, rise to drop, rise to stable and so on. The probabilities can be derived using the estimation procedures below:

$$r = \frac{\sum \Pr}{\sum \Pr + \sum \mathrm{Pd} + \sum \mathrm{Ps}}$$

$$d = \frac{\sum \mathrm{Pd}}{\sum \Pr + \sum \mathrm{Pd} + \sum \mathrm{Ps}}$$

$$s = \frac{\sum \mathrm{Ps}}{\sum \Pr + \sum \mathrm{Pd} + \sum \mathrm{Ps}}$$

$$rr = \frac{\sum \Pr r}{\sum \Pr r + \sum \Pr d + \sum \Pr s}$$

$$rd = \frac{\sum \Pr d}{\sum \Pr r + \sum \Pr d + \sum \Pr s}$$

$$rs = \frac{\sum \Pr s}{\sum \Pr r + \sum \Pr d + \sum \Pr s}$$

$$dr = \frac{\sum Pdr}{\sum Pdr + \sum Pdd + \sum Pds}$$

$$dd = \frac{\sum Pdd}{\sum Pdr + \sum Pdd + \sum Pds}$$

$$ds = \frac{\sum Pds}{\sum Pdr + \sum Pdd + \sum Pds} \sum$$

$$sr = \frac{\sum Psr}{\sum Psr + \sum Psd + \sum Pss}$$

$$sd = \frac{\sum Psd}{\sum Psr + \sum Psd + \sum Pss}$$

$$ss = \frac{\sum Pss}{\sum Psr + \sum Psd + \sum Pss}$$

The Markov Chain Model

In this section, the possible price movement of a stock are modeled as a three-state of nature (rise, drop and stable) Markov Chain with the sum of the probabilities equaling one. The three states are captured in an initial probability vector which gives the probability of the stock price being in a particular state. The transition probability which gives the probability of the system transiting from state to state is also given.

To compute the probability of the system (stock price) being in the next state, we used matrix multiplication laws to derive the product of the initial probability vector (matrix) and the transition matrix. On the basis of the result derived an attempt was made to predict the possible future price direction of the stocks selected for the study. Since we are concerned with investigating the long run price movement mechanism of stocks quoted in the stock exchange, we define the long run probability vectors as follows:

$W_o = [W_r \quad W_d \quad W_s]$

Also,

$$P = \begin{pmatrix} P_{rr} & P_{rd} & P_{rs} \\ P_{dr} & P_{dd} & P_{ds} \\ P_{sr} & P_{sd} & P_{ss} \end{pmatrix}$$

This gives us three equations with three unknowns,

$W_r * P_{rr} + W_d * P_{dr} + W_s * P_{sr} = W_r \rightarrow$

$W_r (P_{rr} - 1) + W_d * P_{dr} + W_s * P_{sr} = O$

$W_r * P_{rd} + W_d * P_{dd} + W_s * P_{sd} = W_d \rightarrow$

$W_r * P_{rd} + W_d (P_{dd} - 1) + W_s * P_{sd} = O$

$W_r * P_{rs} + W_d * Pds + W_s * P_{ss} = W_s \rightarrow$
$W_r * P_{rs} + W_d * P_{ds} + W_s (P_{ss} - 1) = O$

But
$W_r + W_d + W_s = 1$

Therefore,
$W_r (P_{rr} - 1) + W_d * P_{dr} + W_s * P_{sr} = O \rightarrow$
$W_r (P_{rr} - 1) + W_d * P_{dr} + P_{sr} (1 - W_r - W_d) = O$

$\therefore W_r (P_{rr} - P_{sr} - 1) + W_d (P_{dr} - P_{sr}) = -P_{sr}$

$W_r * P_{rd} + W_d (P_{dd} - 1) + W_s * P_{sd} = O \rightarrow$
$W_r * P_{rd} + W_d (P_{dd} - 1) + P_{sd} (1 - W_r - W_d) = O$
$\therefore W_r (P_{rd} - P_{sd}) + W_d (P_{dd} - P_{sd} - 1) = -P_{sd}$

Transforming the two equations into matrix form gives the following:

$$\begin{pmatrix} P_{rr} - P_{sr} - 1 & P_{dr} - P_{sr} \\ P_{rd} - P_{sd} & P_{dd} - P_{sd} - 1 \end{pmatrix} \begin{pmatrix} W_r \\ W_d \end{pmatrix} = \begin{pmatrix} -P_{sr} \\ -P_{sd} \end{pmatrix}$$

$$\therefore \begin{pmatrix} W_r \\ W_d \end{pmatrix} = \begin{pmatrix} P_{rr} - P_{sr} - 1 & P_{dr} - P_{sr} \\ P_{rd} - P_{sd} & P_{dd} - P_{sd} - 1 \end{pmatrix}^{-1} \begin{pmatrix} -P_{sr} \\ -P_{sd} \end{pmatrix}$$

$$= \left[(P_{rd} - P_{sd}) (P_{dr} - P_{sr}) - (P_{rr} - P_{sr} - 1) (P_{dd} - P_{sd} - 1)^{-1} \right]$$

$$* \begin{pmatrix} P_{rr} - P_{sr} - 1 \; P_{dr} - P_{sr} \\ P_{rd} - P_{sd} \quad P_{dd} - P_{sd} - 1 \end{pmatrix} P_{sr} \begin{pmatrix} \\ P_{sd} \end{pmatrix}$$

And $W_s = 1 - W_r - W_d$
W_o = Initial Probability Vector
P = Transition Probability Matrix
$W_r = P_r$ = Probability of the Stock Price rising
$W_d = P_d$ = Probability of the stock price dropping
$W_s = P_s$ = Probability of the stock price remaining stable
P_{rr} = Probability of the stock price rising after a previous rise
P_{rd} = Probability of the stock price dropping after a previous rise
P_{rs} = Probability of the stock price remaining stable after a previous rise
P_{dr} = Probability of the stock price rising after a previous drop
P_{dd} = Probability of the stock price dropping after a previous drop
P_{ds} = Probability of the stock price remaining stable after a previous drop
P_{sr} = Probability of the stock price rising after a previous stable state
P_{sd} = Probability of the stock price dropping after a previous stable state
P_{ss} = Probability of the stock price remaining stable after a previous stable state.

Findings

In this section, we present empirical results of the model specified in our methodology. The first task is the determination of the long run initial probability vector and transition probabilities from the derived transition tables (not included in the study otherwise it would be unwieldy); after which the long-run probabilities of the system was computed. The second task is the futuristic empirical assessment of the system, to determine the efficacy of the model in projecting a fairly conservative prediction of the long run prospects and price direction of common stocks. This is shown in table 1.

Table 1: Long-run Probability of the Future Direction/Prospect of Stocks (for Five Banks)

S/N	Bank	$W_o = [W_r \ \ W_d \ \ W_s]$
1.	Access Bank	[0.0016 0.0478 0.9506]
2.	Eco Bank	[0.0339 0.0441 0.9220]
3.	First Bank	[0.0790 0.0942 0.8268]
4.	Intercontinental Bank	[0.1096 0.1156 0.7748]
5.	Union Bank	[0.0415 0.1037 0.8548]

As shown in table 1, Markov Chain is relevant to the analysis of stock prices, since it can serve as a useful tool for making probabilistic statements about future stock price levels. If on the basis of superior probability value in the matrices, you have a precise indication of the direction in which stock prices are headed in the long run; then the model can be used to derive a conservative prediction of security price levels in the long run. From table 1, the price levels of the randomly chosen stock are very much likely to be stable in the long run. When this anticipated future scenario is analysed *parii passu* with the current down turn in the price levels of stocks in the Nigerian bourse, some fruitful revelations can be derived from our empirical results obtained through the Markov Chain model. The Nigerian economy is presently going through some serious economic challenges as a result of the current global economic meltdown.

This has led to a sharp decline in both public and private sector investments as well as a high degree of investor apathy; thus leading to sharp decline in what many investors regarded as previously overpriced stocks in the stock market. The current down turn in the market tend to suggest that the market is correcting itself in a bid to achieve "price discovery" which aims at ensuring that all stocks are purchased and sold at prices which reflect their true or intrinsic worth both in the immediate, short, and long term.

Also, given the fact, from previous trends, that the economy seems to be growing at a relatively low and stable rate. Then it is safe to assume that prices will also only likely move at a slow and stable rate in the long run. If this is so then we should naturally expect the down turn in prices to give way to slow growth which will eventually culminate in long run stable prices within certain price ranges, which may not be as high as the previous price levels (before the downturn in prices began).

Conclusion and recommendations

This study has attempted to explore some of the ways in which the theory of Markov processes may be applied to the analysis of security price movements. It has been shown that both the possible states of nature of security prices and the nature of its successive price movements may be interpreted within the framework of Markov theory; in such a way as to provide useful information to the portfolio manager.

The paper examined five (5) randomly chosen banks that are quoted on the floor of the Nigerian Stock Exchange (NSE). This was with the aim of predicting the probable long-run prospect of stocks in the Nigerian bourse, wholly on the basis of past price information. The empirical results suggest that prices are likely to be stable in the long run.

However, just as is the case with every long range projection, the possible future occurrence is fraught with many probabilities and only time can prove whether the projections are valid or not. We are however content with the mere fact that we have attempted to add to the very rich, and often conflicting literature on stock price prediction or behaviour. It is our sincere belief that the techniques provided here will add to the very rich store of methods adopted by technicians (technical analyst) in arriving at long range projections on the future prospect of stocks in the stock market. Another strong point of the method adopted here is that it considers the possible states that can be adopted by stock prices at any particular point in time which makes not only the analysis to be more robust but also the findings to be interestingly revealing.

Furthermore, in the long run, and also irrespective of the current global economic melt-down, which has currently led to a down turn in stock prices on the floor of the nation's bourse our Markov Chain model suggests that prices will remain stable. This may be suggestive that the current down turn in stock prices will eventually give way to stability in price levels over the long run. What is however not known is if the stable price situation will be at the current low price levels or at the previous peak price levels.

The use of Markov Chains in portfolio analysis is a virtually unexplored field and a very promising one. The results and methods presented here are very rudimentary and should be interpreted solely as illustrations. Much work needs to be done on such refinements as a Bayesian – type updating of the transition probability matrix (TPM) and on refinements of the model before the results could be given any operational validity.

Finally, the long run prospects of stock prices in Nigeria, as investigated and discussed in the study, may serve as very useful spring board for some other less developed countries (LDC's) or added experience for some others. This is more so, as there is need to confirm or refute many of the findings on stock price prediction and behaviour. Surely empirical work has unearthed some stylized facts on this very controversial area of finance; but this evidence is largely based on stocks quoted in American and European bourses, and it is not at all clear how these facts relate to different theoretical models of other countries. Without testing the robustness of these findings outside the environment in which they were uncovered, it is hard to determine whether these empirical regularities are merely spurious correlations, let alone whether they support one theory or another. It is thus our sincere desire that similar works of this nature be done in LDC's (Nigeria inclusive) as an attempt to start filling this gap in our knowledge.

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