TIME SERIES PATTERNS OF SRI LANKAN STOCK RETURNS

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ABSTRACT

Predicting the future was one of the strongest desires of man. The actualization of the desires historically began with astrology paying the path for scientific predictions and forecasting. Scientific forecasting in financial markets also has a long history going back to 1950's. Literature shows several attempts in modeling share returns in Sri Lankan context, but outcomes of the studies were not satisfactory. Colombo Stock Exchange (CSE) is a population containing 20 mutually exclusive subsets (sectors). Elements of these subsets are homogeneous in nature of business. As such, there may be similarities in market performances within groups and similar forecasting techniques may successful in forecasting. Present study was focused on sector wise pattern recognition of returns and identifying suitable time series forecasting techniques. Random sample of four business sectors were selected and required data were obtained from CSE data library, 2011. Box- Plots of returns and one –way ANOVA were used for comparison of returns within and between sectors. Results did not give evidence for significant differences in mean returns. Time series plots of returns of individual companies as well as sectors showed no trends. Stationary of the series were tested by Auto Correlation Functions (ACF's) and found all the series stationary. Based on the results it was concluded that company returns as well as sector returns of CSE were stationary. It is recommended to test ARIMA models and Spectral Analysis in forecasting returns of Sri Lankan share market.

Keywords: Stationary, ANOVA, ARIMA, Spectral Analysis

INTRODUCTION

Predicting the future was one of the strongest desires of man, which may have begun with the beginning of time. Predictions were immense importance to the man at individual levels as well as in general. For examples, individuals were interested in foreseeing their own future. Society was keen in predicting weather conditions. The actualization of those goals; historically begun with fortune telling, astrology, palmistry etc. paving the path for scientific predictions and forecasting. Over the past hundreds of years, scientific predictions and forecasting extended horizons to natural sciences as well as social sciences.

Scientific forecasting is based on mathematical modeling. A mathematical model is a simplification of a real world situation into an equation or a set of equations. Process of designing a mathematical model is split into several stages. They are; a real world problem is observed, a mathematical model is devised, real world experimental data is collected, real world expected behavior is predicted by mathematical model, predicted and observed outcomes are compared and the mathematical model is refined (if necessary).

Mathematical models have many classifications; "Deterministic models Vs Stochastic models" is one of them. A deterministic model is one in which every set of variable states is uniquely determined by parameters in the model and by sets of previous states of these variables. Deterministic models are not associated with any randomness, therefore less realistic. A model which randomness is present and variable states are described by associated probability distributions is called stochastic model. In general stochastic models are known as statistical models.

Time Series Analysis

Time series analysis is a branch of statistical analysis. A time series is a sequence of observations, usually ordered in time. The feature of time series analysis which distinguishes it from other statistical analyses is the explicit recognition of the importance of the order in which the observations are made (Anderson, 1971). There are various purposes for using time series. Some of them are; prediction of the future based on knowledge of past, to understand the mechanism of generating the series and to control the process producing the series.

Time series methods can be divided into two parts; Univariate methods and Multivariate methods. Univariate methods use the past internal patterns in data to forecast the future and no external variables are required in forecasting. The basic concept of these methods is that future values of a series are a function of past values. Univariate methods include moving average smoothing, exponential smoothing, decomposition techniques, Fourier series analysis, Box Jenkin's ARIMA methods, linear and non linear trend models (Stephen, 1998). Multivariate models make projections of the future by modeling the relationship between a series and the other series. It models future values of a series as a function of itself and values of other variables. Multivariate Regression, Multivariate ARIMA (MARIMA), Vector Auto Regression (VAR) are some of the multivariate techniques. Research and management of large number of fields such as agriculture, medicine, engineering, physics, econometrics, social sciences, marketing, finance, hospitality and tourism and many more rely on time series modeling and use them for prediction, control and optimization.

Time Series Forecasting in Financial Markets

Scientific forecasting in financial market has a history going back to 1950's. First recorded successful model was a multivariate statistical model, known as Capital Asset Pricing Model (CAPM). Since then, both types of statistical models; univariate and multivariate have been in practice all over the world in forecasting stock returns.

Sri Lankan stock market also relies on Capital Asset Pricing Model (CAPM). However, forecasting ability of CAPM was in debate in last decades. Nimal (1997), Samarakoon (1997) and Konarasinghe & Abeynayake (2014) have given evidences for the inability of CAPM in Sri Lankan share market. According to literature, there were several attempts to forecast Sri Lankan share market returns. Most of them were applications of multivariate statistical methods and few of them were univariate ARIMA methods and artificial neural network. But outcomes of the studies were not up to the level of satisfactory. Rathnayaka, Seneviratna, & Nagahawatta, (2014) have attempted to identify patterns and trends in stock prices and trading volumes of CSE in order to spot any groups of stocks that exhibit similar behaviors. It was a very good starting point, because identification of time series patterns and covariance structure of the market is the key to success in modeling. However, Rathnayake *et al* was unable to find any such patterns, trends or covariance in share prices or trading volume.

Stock market is a partition; a population containing mutually exclusive subsets. For example, Colombo Stock Exchange (CSE) has 20 business sectors or 20 subsets. These subsets are defined in a way that they are mutually exclusive and the elements of these subsets (listed companies of these sectors) are homogeneous in nature of business. As such there may be similarities in market performances within groups and there may be differences between groups. If there are similarities, then similar forecasting techniques may be successful in forecasting. On view of those, present study was focused on; pattern recognition of individual company returns, identification of similarities and differences in returns of individual company returns sector wise, pattern recognition of sector returns, identification of similarities and differences in patterns of sector returns and spotting suitable time series forecasting techniques.

Significance of the study

Share trading is an important part of the economy of a country from both the industry's point of view as well as the investor's point of view. For example, whenever a company wants to raise funds for further expansion or settling up a new business venture, instead of taking loans it can issue shares of the company. On the other hand an investor can get the part ownership of the company through buying shares. This gives him/ her vote at annual shareholder meetings, and a right to a share of future profits. Investors have the ability to quickly and easily sell securities. This is an attractive feature of investing in stocks, compared to other less liquid investments such as real estate. From the point of view of economy in general, a healthy stock market has been considered indispensable for economic growth and is expected to contribute to improvement in productivity. According to the literature, researchers have not reached up to a satisfactory level in forecasting returns of individual companies or sectors in Sri Lankan context. Hence this study will pave the path for academics and researchers to find reliable forecasting techniques for Sri Lankan share market.

Literature Review

Literature review is divided into two parts;

i. Time Series Forecasting Methods

ii. Applications of time series models in financial markets.

Time Series Forecasting Methods

Time Series is a sequence of measurements that follow non random order, taken sequentially in time. Time Series Techniques have several branches such as; Trend Analysis, Smoothing Techniques, Decomposition Techniques, Stochastic Process and Fourier analysis.

Trend Analysis

Trend of a time series is the long term increasing or decreasing pattern of a time series. It can be either linear or non-linear. Trend can be identified by semi- average method or least square method.

Smoothing Techniques

Smoothing techniques can be used to short term forecasting or to remove the fluctuations of a series. Well known Smoothing techniques are; Moving Average Smoothing, Single Exponential Smoothing, Double Exponential Smoothing and Winters' Method. Moving Average smoothes the data by averaging consecutive observations in a series and provides short-term forecasts. This procedure can be a likely choice when the data do not have a trend or seasonal component.

Single exponential smoothing smoothes data by computing exponentially weighted averages and provides short-term forecasts. This procedure works best for data without a trend or seasonal component. Double exponential smoothing smoothes data by Holt (and Brown as a special case) double exponential smoothing and provides short-term forecasts. This procedure can work well when a trend is present but it can also serve as a general smoothing method. Dynamic estimates are calculated for two components: level and trend. Winters' Method smoothes data by Holt-Winters exponential smoothing and provides short to medium-range forecasting. Winters' Method calculates dynamic estimates for three components: level, trend, and seasonal.

Decomposition Techniques

Forecasting via classical time series methods may be viewed as an attempt to decompose the series into component parts and then predict the future pattern of each part. Decomposition techniques assume four components of a time series; Trend component (T), Cyclical component (C), Seasonal component (S), and Irregular component (I). Trend component of a time series is the long term increasing or decreasing pattern. Cyclical component is the long term wave like pattern, which has a wave length longer than one year. Seasonal component is also a wave like pattern, but occurs within a year and has a wave length shorter than one year. Irregular component is the random error.

Decomposition techniques have two models including the above components. They are;

Multiplicative model:

$$Y = T.S.C.I \tag{1}$$

And, Additive model:

$$Y = T + S + C + I \tag{2}$$

Stochastic Process

A stochastic process or a random process X(t),$t \in$ T}is a family of random variables where the index set *T* may be discrete (*T* ={0,1,2,}) or continuous (*T* =[0,∞)). A *stationary process is a special case of stochastic process.*

Stationary Process

A sequence $\{x_t\}$ is a white noise process or stationary process if each value in the sequence has

i. Zero-mean $E(x_t) = E(x_{t-1}) = .. = 0$

ii. Constant conditional variance $E(x^2{}_t) = E(x_{t-1}{}^2) = ..\sigma^2 = Var(x_{t-i})$

iii. Is uncorrelated with all other realizations $E(x_t x_{t-s}) = E(x_{t-j} x_{t-j-s}) = .. = 0 = Cov(x_{t-j} x_{t-j-s})$

General Linear Processes (GLP)

A General Linear Process is a stationary stochastic process $\{X_t\}$ which can be represented as weighted linear combination of the present and past terms of a white noise. General Linear Models or linear time series model are designed specifically for modeling the dynamic behavior of time series. These include Auto Regressive (AR), Moving Average (MA), Auto Regressive Moving Average (ARMA), Auto Regressive Integrated Moving Average (ARIMA) models.

These time series models are useful for a variety of reasons;

i. Modeling the serial correlation in the disturbances of a regression model.

ii. Out-of-sample forecasting (Univariate; Multivariate).

iii. Providing information about the dynamic properties of a time series variable.

iv. The vector versions of these models have become much more prominent than traditional simultaneous equation systems for studying the structural relationships in macroeconomic systems.

The basic building block in time General Linear models is the white noise process, $\{\varepsilon_t\}$:

$E(\varepsilon_t) = 0$ for all t

$E(\varepsilon_t^2) = \sigma^2 > 0$ for all t

$E(\varepsilon_t \varepsilon_{t-s}) = 0$ for all t for all $s \neq 0$

ARp Process

Auto Regressive Process {Y_t} of order p has the model;

$$Y_t = c + \sum_{i=1}^{p} \Phi_i Y_{t-i} + \varepsilon_t$$

(3)

Where Y_{t-i} are past observations of random variable Y_t.

MA_q Process

Moving Average Process {Yt} of order q has the model;

$$Y_t = \mu + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}$$

(4)

Where ε_{t-i} are past errors of random variable Y_t.

ARMA Model

A model containing both AR and MA parts is known as mixed model or Auto Regressive Moving Average (ARMA) model. ARMA (p,q) model is:

$$Y_t = c + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \sum_{i=1}^{p} \varphi_i Y_{t-i}$$

(5)

ARMA model is not valid if the series is not stationary, therefore, differences are taken in order to achieve stationary and order of difference is given by d. Then the model is called Auto Regressive Integrated Moving Average or ARIMA (p,d,q) model which is given by the formula;

$$\phi_p(B)\Delta^d Y_t = \theta_q(B)\varepsilon_t$$

(6)

Where, B is the back shift operator.

Fourier Series Analysis

Fourier Series Analysis (FSA) is also known as Spectral Analysis or Harmonic Smoothing. FSA has been developed for and is extensively used in the field of engineering and physics in order to identify the patterns of alternating current, vibrating springs etc. FSA represent these periodic observations by a series of trigonometric functions of sines and cosines. Later it has been applied to describe the seasonal and cyclical patterns of a time series.

Fourier Series Analysis has a model;

$$Y_t = A.\,Sin\,(\omega\, t + \alpha)$$
(7)

Where, Y_t= value of the time series at time t.

A= amplitude or intensity of the series.

α= phase shift that determines the horizontal position of the repeating pattern.

$\omega = \dfrac{2\pi f}{n}$; frequency (number of peaks or troughs in n observations)

Applications of Time Series Models in Financial Market

Scientific forecasting methodologies of stock returns fall into two broad categories. They are fundamental analysis and technical analysis. Fundamental analysis is based on economic factors or characteristics of a company such as; company value, company earnings etc. while technical analysis is based on past returns and trading volumes of a company. In other words technical analysis relies on time series techniques. According to Konarasinghe & Pathirawasam (2013), linear regression modes, non linear regression models, Vector Auto Regression (VAR) Models, and multivariate causal models have been tested in large number of markets and were successful. Among them mainly tested models were multivariate causal models. Konarasinghe & Pathirawasam (2013) also tested them for Sri Lankan context, but was not successful in forecasting returns. ARIMA models have been tested on forecasting returns by Jeffrey & Eric (2011), Rosangela , Ivette , Lilian & Rodrigo ( ), Konarasinghe & Abeynayake (2014) and many others. According to literature, Spectral analysis has been tested only by Granger & Morgenstern (1963), but that also was not successful.

METHODOLOGY

Listed companies of CSE were the population of study. The population consist 20 subsets (business sectors), they were; Plantation (PLT), Oil palms (OIL), Land and Property (L&P), Motors (MTR), Manufacturing (MFG), Telecommunication (TLE), Stores supplies (S&S), Trading (TRD), Services (SRV), Power and energy (P&E), Investment trust (INV), Hotels and Travels (H&T), Heath care (HLT), Footwear and Textile (F&T), Information Technology (IT), Diversified Holdings (DIV), Construction and engineering (C&E), Chemicals and Pharmaceuticals (C&P), Beverage Food and Tobacco (BFT), Bank and Finance and Insurance (BFI). Multi- stage sampling technique was adopted in sample selection; in stage 1 four sectors were chosen randomly and in stage 2, three companies from each selected sector were chosen randomly. Daily closing share price data and monthly sector indices were obtained for the period 1998 - 2011 from CSE data library 2011. Total sample size was 12 and the sample of the study is given in table1.

Table 1 Sample of the study

Sector	Companies
BFI	Commercial Bank (COMBANK), Sampath Bank (SAMPATH), Hatton National Bank (HNB).
PLT	Agalawatte Plantation Limited (AGALA), Bogawantalawa Tea Estate Limited (BOGAW), Watawala Plantations PLC (WATAW).
BFT	Distilleries Company of Shri Lanka Ltd. (DISTILLERS), Nestle Lanka PLC (NESTLE), Ceylon Brewery PLC (BREW).
DIV	John Keells Holdings PLC (JKH), Hayleys PLC, Richard Pieris PLC (RICHARD).

Daily returns for each company were calculated by formula;

$$R_t = \left(\frac{P_t - P_{t-1}}{P_t} \right) 100$$

(8)

Where; P_t is the daily closing price. Monthly average returns were obtained using daily returns.

Monthly sector returns were calculated by formula;

$$R_M = \left(\frac{I_t - I_{t-1}}{I_t} \right) 100$$

(9)

Where I_t is the sector index of month t.

Box- plots, time series plots and Auto Correlation Functions (ACF) were used for pattern recognition. One way- Analysis of Variance (ANOVA) was used for mean comparison of returns.

DATA ANALYSIS

Data analysis is organized sector wise as;

i. Pattern recognition of sector –BFI.

ii. Pattern recognition of sector –PLT.

iii. Pattern recognition of sector –BFT.

iv. Pattern recognition of sector –DIV.

v. Comparison of Sector returns.

Statistical software Minitab is used for data analysis. Outliers of all the data series were removed with the help of Box plots and the outlier free data were used in data analysis.

Pattern Recognition of Sector BANK, FINANCE & INSURANCE (BFI)

Figure1 is the Box-Plot for monthly returns of Commercial Bank (COMBANK), Sampath Bank (SAMPATH), Hatton National Bank (HNB), Bank and Finance and Insurance sector (BFI).

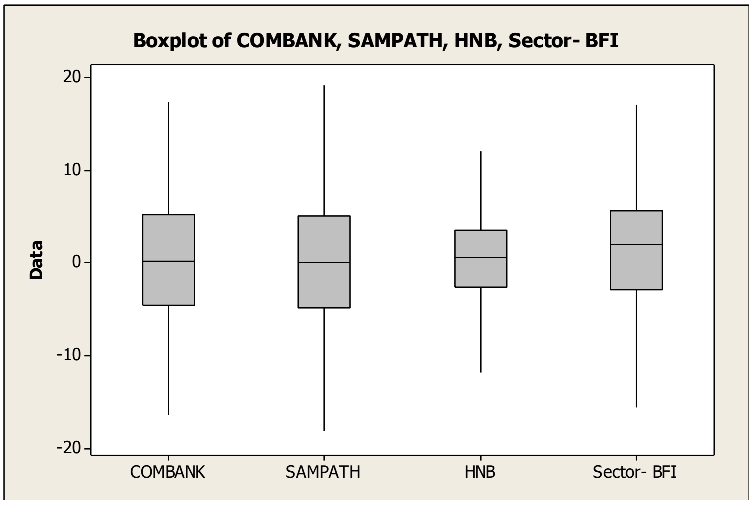


Figure 1 Box- Plot of Returns of BFI Sector and Companies

According to Figure 1, returns of individual companies as well as sector were symmetrically distributed. Dispersion of returns of HNB is less than the others, but average returns of all of them looked similar.

Analysis of Variance (ANOVA) was used for the following mean comparison;

H_0: $\mu_{COMBANK} = \mu_{HNB} = \mu_{SAMPATH} = \mu_{SECTOR}$

H_1: At least one mean is different from the others.

P value of one-way ANOVA = 0.570, was not significant at 5% significance level. Therefore, it was concluded that mean returns of individual companies and sector were not different.

Figure 2, Figure 3, Figure 4 and Figure 5 are the time series plots of returns of BFI sector, COMBANK, SAMPATH and HNB respectively.

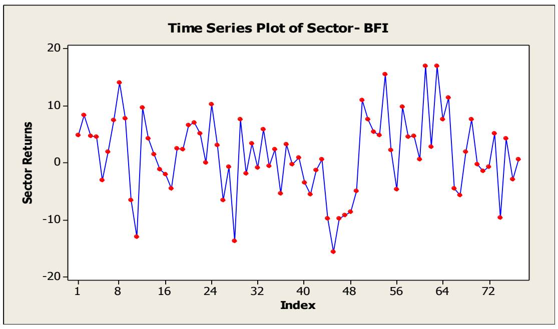


Figure 2 Time Series plot of BFI

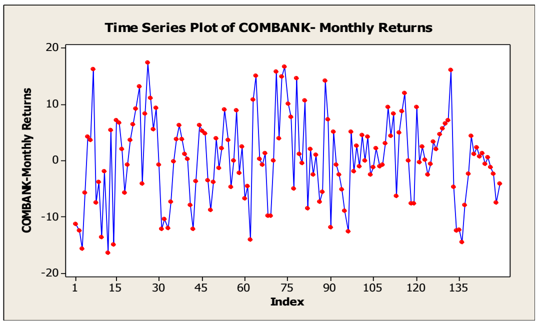
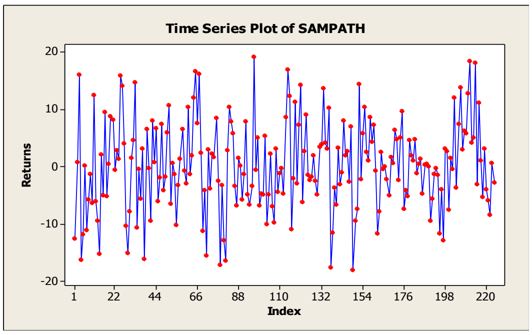


Figure 3 Time Series plot of COMBANK



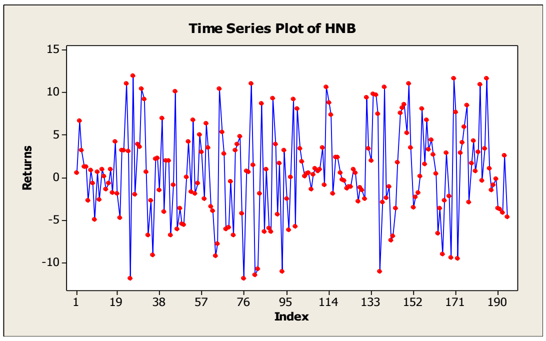
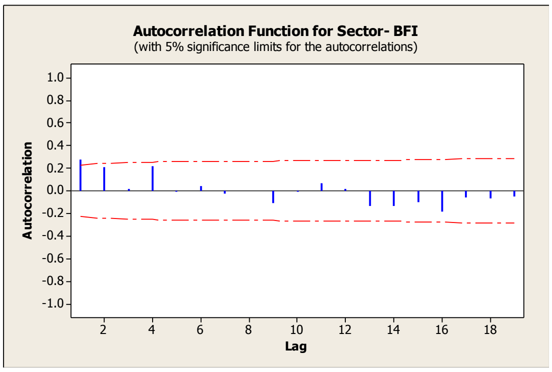


Figure 4 Time Series plot of SAMPATH

Figure 5 Time Series plot of HNB

Time series plots did not show any trend in returns, but showed wave like patterns. Returns of all four figures fluctuated around some value and suggested stationary of series. Therefore, ACF's were obtained for returns. Figure 6**,** ACF of sector returns has a significant spike at lag 1. It showed that returns of sector BFI were stationary.



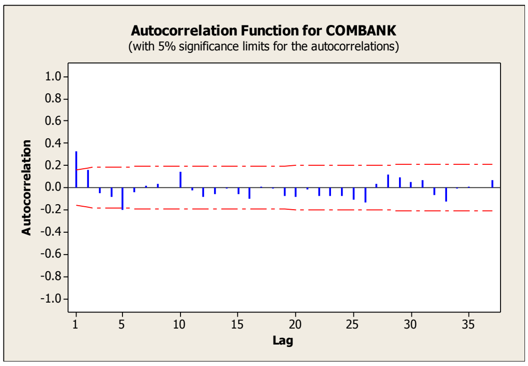
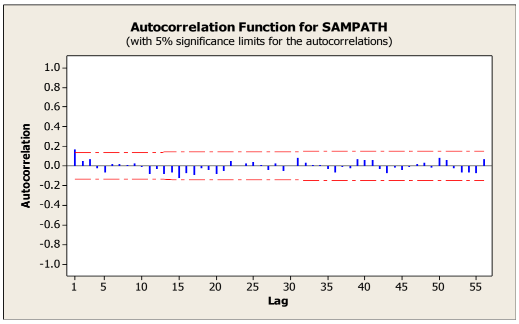


Figure 6 ACF of sector returns

Figure 7 ACF of COMBANK returns

Similarly Figure 7, Figure 8 and Figure 9 confirmed that return series of individual companies is also stationary.



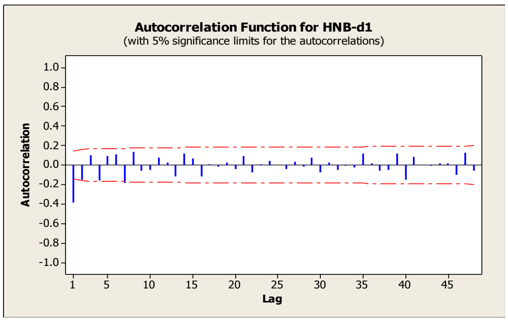


Figure 8 ACF of SAMPATH

Figure 9 ACF of HNB

Above results confirmed that returns of BFI sector and its individual companies were not significantly different and returns were stationary type. Therefore, similar forecasting methods may be successful in forecasting returns.

Pattern Recognition of Sector PLANTATION (PLT)

Figure 10 is the Box- Plot of returns of plantation sector and individual companies of the sector.

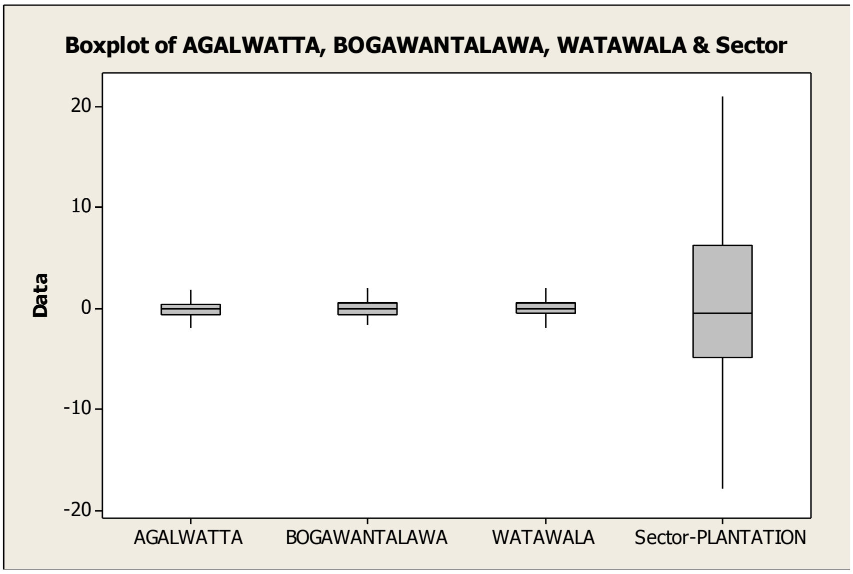


Figure 10 Box- Plot of Returns of PLT Sector and Companies

Figure 10 shows a clear difference in spread of returns between individual companies and the sector. But average returns did not show a clear difference. Analysis of Variance (ANOVA) was used for the following mean comparison;

H_0: $\mu_{AGALAWATTA} = \mu_{BOGAWANTALAWA} = \mu_{WATAWALA} = \mu_{SECTOR}$

H_1: At least one mean is different from others.

P value of one-way ANOVA = 0.615, was not significant at 5% significance level. Therefore, it was concluded that mean returns of individual companies and sector were not different.

Figure 11, Figure 12, Figure 13 and Figure 14 are the time series plots of returns of plantation sector and sample of companies of the sector.

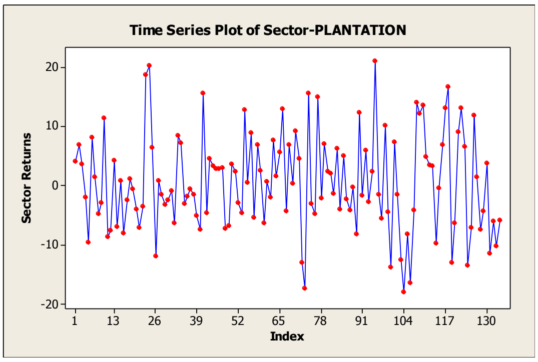


Figure 11 Time Series plot of PLANT

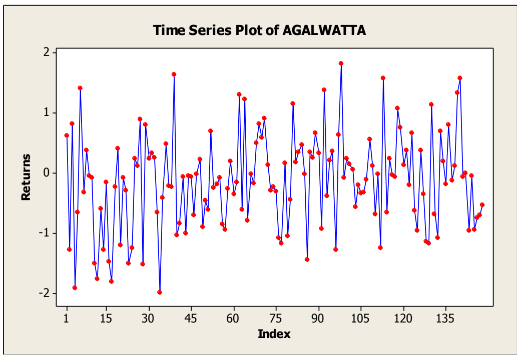
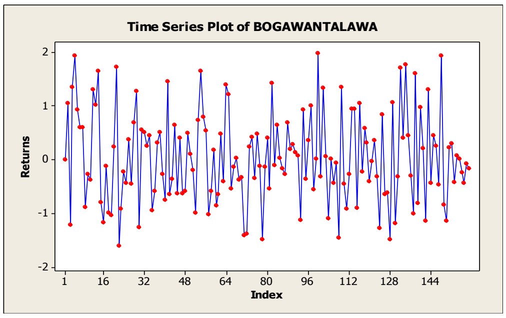


Figure 12 Time Series plot of AGALA



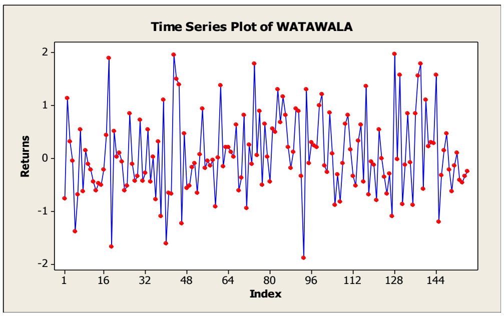
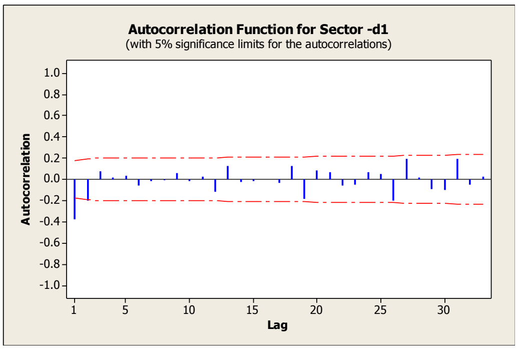


Figure 13 Time Series plot of BOGAW

Figure 14 Time Series plot of WATAW

Time series plots did not show any trend in returns, but showed wave like patterns. Returns of all four figures fluctuated around some value and suggested stationary of series. Therefore, ACF's were obtained for returns and found non- stationary in original series. Then first difference series were considered and Figures 15-18 are the ACF's of first difference series. All four ACF's have significant spikes at lag 1 and got confirmed the stationary of returns.



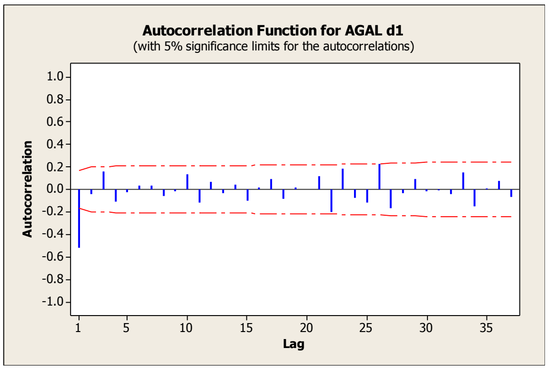
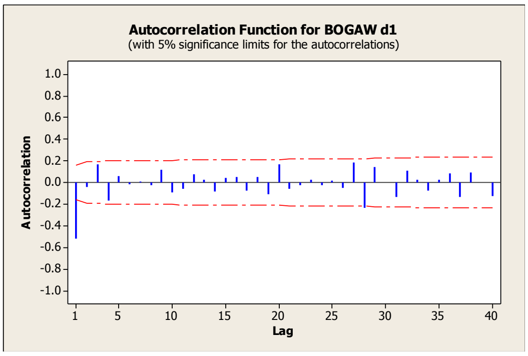


Figure 15 ACF of Sector-PLANT

Figure 16 ACF of AGALA



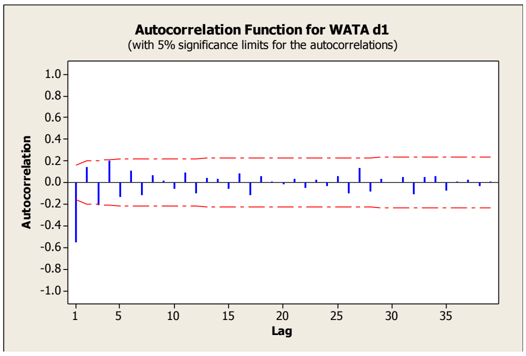


Figure 17 ACF of BOGAW

Figure 18 ACF of WATAW

Above results confirmed that returns of plantation sector and its individual companies were not significantly different and returns were stationary type. Therefore, similar forecasting methods may be successful in forecasting returns.

Pattern Recognition of Sector Beverage Food and Tobacco (BFT)

Figure 19 is the Box- Plot of returns of BFT sector and individual companies of the sector.

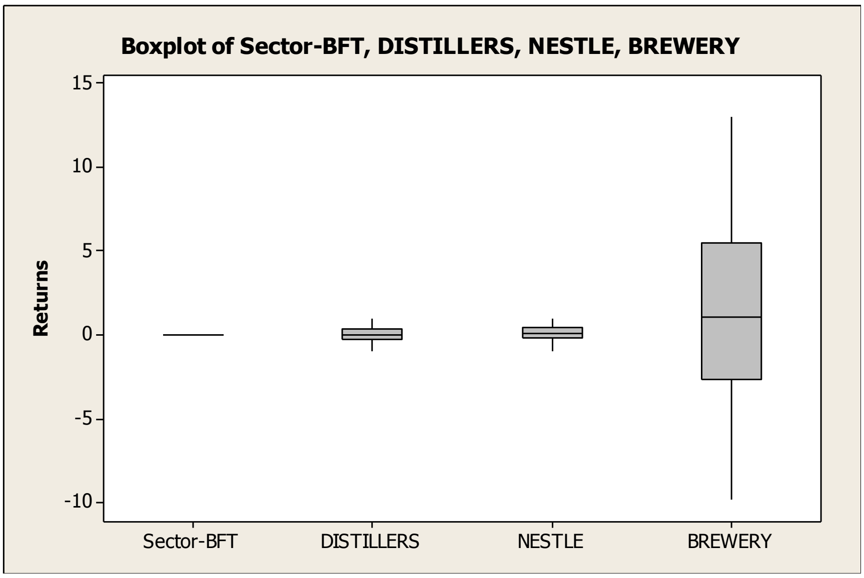


Figure 19 Box- Plot of Returns of BFT Sector and Companies

Figure 19 showed that the average returns of BFT sector is almost zero. Two companies DISTILLERS and NESTLE have similar distributions of returns while BREWERY has higher variation in returns.

Analysis of Variance (ANOVA) was used for the following mean comparison;

H_0: $\mu_{BFI} = \mu_{DISTILLERS} = \mu_{NESTLE} = \mu_{BREWERY}$

H_1: At least one mean is different from others.

P value of one-way ANOVA = 0.000, was significant at 5% significance level. Therefore, it was concluded that at least one mean is different from the others. Individual 95% Confidence Interval (CI) for mean based on pooled standard deviation was obtained and given in Table 2;

Table 2 95% CI for Mean Returns of Sector-BFT and Companies

```
Individual 95% CIs For Mean Based on Pooled Standard Deviation

Level          N    Mean   StDev  -+---------+---------+---------+--------
Sector-BFT    70   0.779   2.513             (-----------*----------)
DISTILLERS   229   0.110   0.611             (-----*-----)
NESTLE       240  -1.464   5.356  (-----*-----)
BREWERY      119   0.925   8.123                  (-------*--------)
                                  -+---------+---------+---------+--------
                                  -2.0      -1.0       0.0       1.0

Pooled StDev = 4.815
```

95% confidence interval of BREWERY did not contain zero. It confirmed that returns of BREWERY were superior to others.

Figure 20, Figure 21, Figure 22 and Figure 23 are the time series plots of returns of BFT sector and sample of companies of the sector.

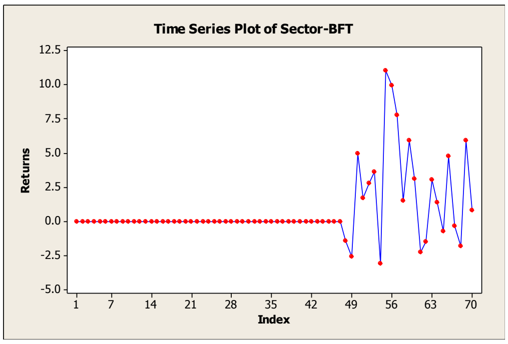


Figure 20 Time Series plot of BFT

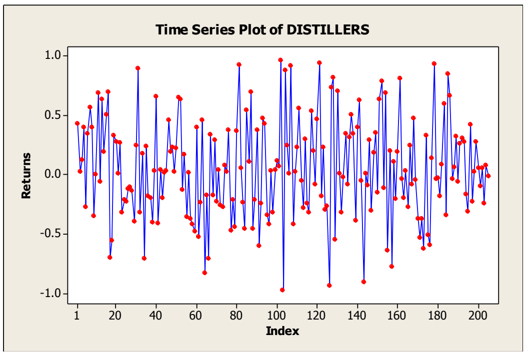


Figure 21 Time Series plot of DISTIL

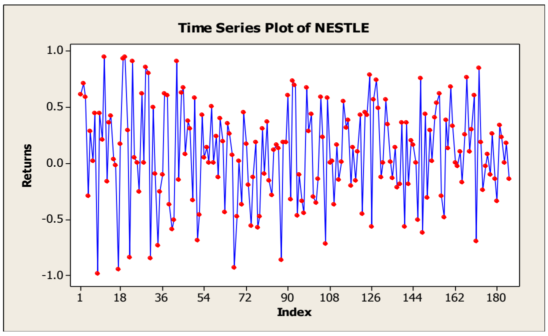


Figure 22 Time Series plot of NESTLE

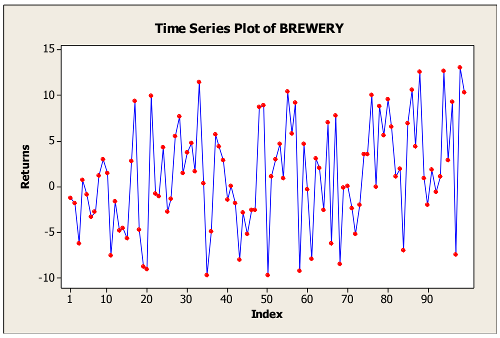


Figure 23 Time Series plot of BREW

Time series plot of BFT is different from others. Figure 20 showed that the returns of BFT were zero for more than two thirds of the series. All four time series plots did not show any trend in returns, but showed wave like patterns, especially in returns of individual companies. Returns of companies fluctuated around some value and suggested stationary of series. ACF's of first difference series confirmed the stationary of returns. Above results confirmed that returns of sector as well as individual companies were stationary type. Therefore, similar forecasting methods may be successful in forecasting returns of individual companies and sectors.

Pattern Recognition of Sector Diversified Holdings (DIV)

Figure 24 is the Box-Plot for monthly returns of sector DIV and sample of companies.

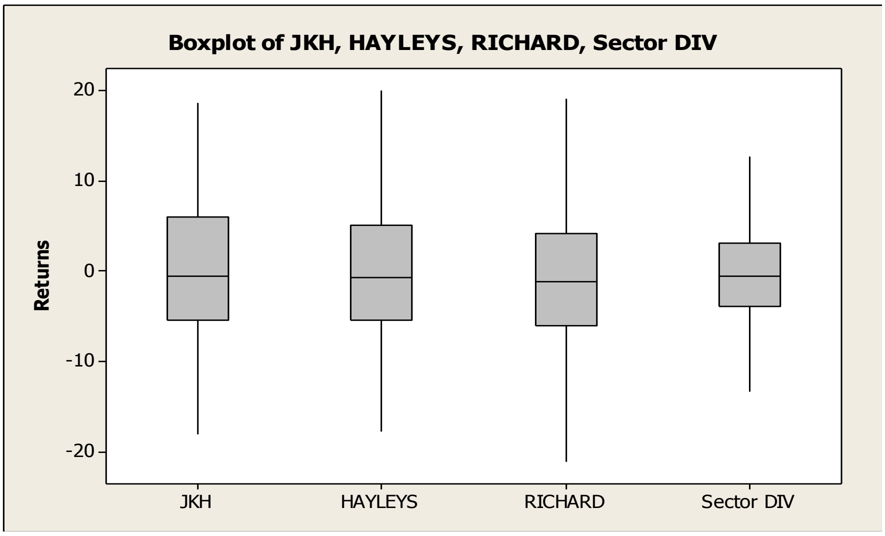


Figure 24 Box-Plot for monthly returns of sector DIV and companies.

According to Figure 24, returns of sector and individual companies have symmetrical distributions. Spread of DIV was less than the others, but average returns of all four looked similar. P value of one –way ANOVA for mean comparison (P=0.867) was greater than α=0.05. It confirmed no difference in means of all four.

Figure 29, Figure 30, Figure 31 and Figure 32 are the time series plots of returns of BFT sector and sample of companies of the sector.

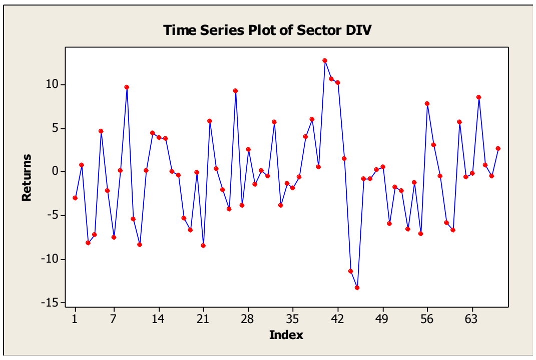


Figure 25 Time Series plot of DIV

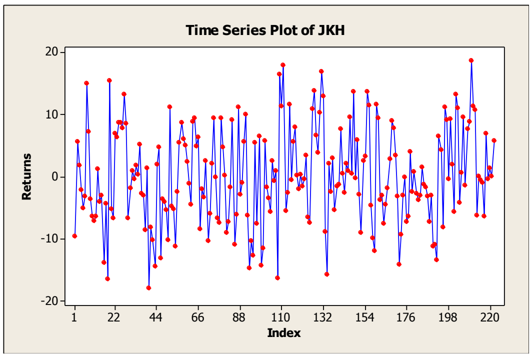


Figure 26 Time Series plot of JKH

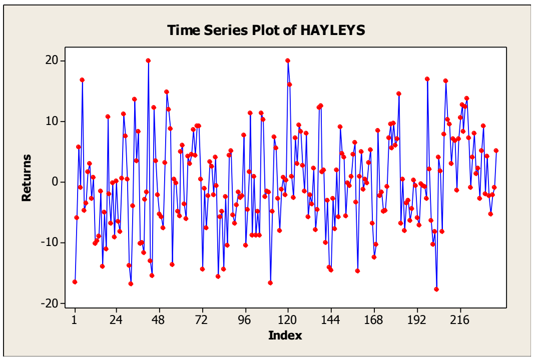


Figure 27 Time Series plot of HAYLEYS

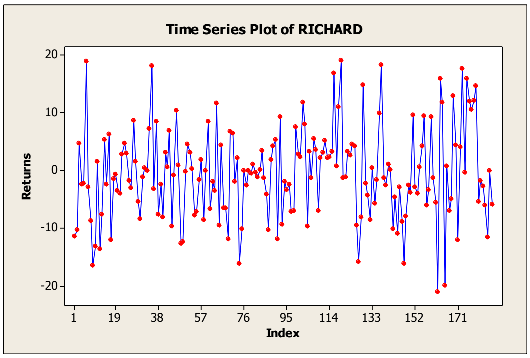


Figure 28 Time Series plot of RICHAD

Time series plots did not show any trend in returns, but showed wave like patterns. Returns of all four figures fluctuated around some value and suggested stationary of series. Therefore, ACF's were obtained and found stationary in returns of sector as well as individual companies. Similar forecasting methods may be successful in forecasting returns of individual companies as well as the sector due to the similar behavior of returns.

Comparison of Sector returns.

Figure 29 is the Box- Plot of returns of four sectors; BFI, PLANT, BFT and DIV

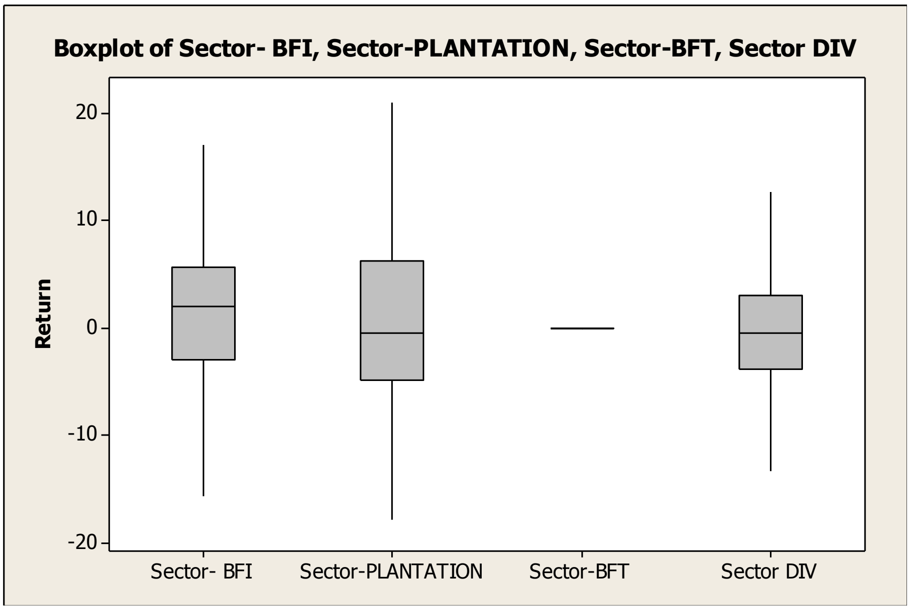


Figure 29 Box- Plot of Returns of Sectors BFI, PLANT, BFT and DIV

Figure 29 showed differences in spread of returns, but did not show differences in average returns. One-way ANOVA was used for mean comparison of returns. P value (0.417) of the test was greater than α (0.05), gave evidence for no difference in mean returns of four sectors. Also time series plots of sector returns, Figure 2, Figure 11, Figure 20 and Figure 25 showed no trend, but showed wave like patterns. ACF's of returns of all four sectors confirmed stationary of returns. Therefore, similar forecasting methods may be suitable in forecasting returns of all four sectors.

CONCLUSIONS AND RECOMMENDATIONS

Scientific forecasting has been playing a vital role in forecasting share returns all over the world. Scientific forecasting is based on mathematical modeling and statistics make mathematical model more realistic. Time series analysis is a branch of statistical analysis. A time series is a sequence of observations, usually ordered in time. The feature of time series analysis which distinguishes it from other statistical analyses is the explicit recognition of the importance of the order in which the observations are made (Anderson, 1971).

Present study was focused on pattern recognition of share returns of Sri Lankan share market and objectives of the study were; pattern recognition of individual company returns, identification of similarities and differences of individual company returns sector wise, pattern recognition of sector returns, identification of similarities and differences of sector returns and spotting suitable time series forecasting techniques.

Listed companies of CSE were the population of study which consists of 20 subsets (business sectors). Multi- stage sampling technique was adopted in sample selection; in stage 1 four sectors were chosen randomly. Selected sectors were BFI, PLANTATION, BFT and DIV. In stage 2, three companies from each selected sector were chosen randomly. Daily closing share price data and monthly sector indices were obtained for the period 1998 - 2011 from CSE data library 2011. Box-Plots, Time Series Plots and ACF’s were used for pattern recognition of returns. One way ANOVA was used for mean comparison of returns.

Results confirmed that returns of sector BFI and its individual companies, sector PLANTATION and its individual companies and sector DIV and its individual companies were not significantly different and returns were stationary type. Mean returns of one company of sector BFT was different from the others, but all return series had the same pattern and they all were stationary type. It was concluded that sector returns as well as individual company returns of CSE have wave like patterns and no trends. Returns of individual companies and sectors can be considered as stationary. Accordingly ARIMA models and Spectral analysis may be suitable in forecasting returns.

ARIMA models and Spectral analysis is recommended in forecasting returns of individual companies and sectors of Sri Lankan share market.

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