FINANCIAL TIME SERIES MODELING ON STOCK MARKET INDICES: A LITERATURE SURVEY

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Abstract: Accurate forecasting of movement of financial indicators as applicable to investing e.g. stock market indices, stock prices, foreign exchange rates etc. has been receiving high importance to scholars of applied finance. Time series analysis is a powerful statistical tool which aids in reliable forecasting of these kinds of financial data which in essence are time series data. There are various available techniques for modeling these financial time series data for forecasting. Novel techniques for such modeling are emerging as a result of continuous research in the field by scholars all over the world. This paper is concerned about survey of literature on the available techniques for such modeling and on the application of such techniques for a comparative study on the efficacy of such techniques in forecasting the respective financial time series. The survey of literature has been kept confined on stock market indices only. This paper identifies certain techniques which are more popular over others in application with an interesting finding that no particular technique can be considered to the ideal one applicable at all periods of time and on all types of time series data. Some novel and lesser used time series modeling methods have been identified which may be tested for their efficacy in forecasting accuracy. Moreover, certain new stock market indices like sectoral and thematic indices, have been identified which may be tested for their suitability for time series modeling.

Keywords: Forecasting, Sectoral & Thematic Indices, Stock Market Indices, Time Series Analysis.

INTRODUCTION

One of the most important problems in modern finance is finding efficient ways to summarize and visualize the stock market data to give individuals or institutions useful information about the market behavior for investment decisions. The enormous amount of data generated by the stock market has attracted researchers to explore this problem using different methodologies. Time series modeling is one such extensively technique used to forecast future movement of stock market indices.

In general, times series forecasting is considered as a highly complex problem, which is particularly true for financial time series. Stock markets have been studied over and over again to extract useful patterns and predict their movements. Moreover, certain new stock market indices like sectoral and thematic indices have come into existence.

Sectoral Indices are indices constructed to reflect performance of a particular sector of the industry. Broad based indices are sector neutral as they are constructed either on the basis of number of stocks used i.e. BSE 100, BSE 200, BSE 500 indices or on the basis of level of capitalization i.e. BSE Sensex, C&P NSE Nifty, BSE Midcap and BSE Small Cap indices. Performance of individual sectors are different from one another and from the broad-based indices. Sectoral indices provide the investors with performance profile of individual sectors of the industry. The prominent sectoral indices in the Indian Stock market include BSE Auto (commencement date: February 1st 1999), BSE Capital Goods (commencement date: February 1st 1999), BSE FMCG (commencement date: February 1st 1999), BSE IT (commencement date: February 1st 1999), BSE Oil & Gas (commencement date: February 1st 1999), BSE PSU (commencement date: February 1st 1999), BSE Technology (commencement date: January 31st 2000), BSE Bankex (commencement date: January 1st 2002), BSE Consumer Durables (commencement date: February 1st 1999), BSE Health Care (commencement date: February 1st 1999), BSE Metal (commencement date: February 1st 1999), BSE power (commencement date: January 3rd 2005)and BSE Realty (commencement date: January 2nd 2006)indices.

On similar thoughts, several thematic indices have been constructed to measure the performance of a groups of organizations which are sector neutral but have a common theme or investment strategies. Themes or specific investment strategies may be various. Examples of such thematic indices include the BSE Carbonex (commencement date: September 30th 2010) which takes a strategic view of organizational commitment to climate change mitigation. This index holistically incorporates strategies, disclosures, performance and action in areas of carbon emission to create a comprehensive benchmark that identifies a company's commitment to mitigate risks arising from climate change. Another example in the Indian scenario is the BSE Greenex (commencement date: October 1st 2008) which is designed specifically to promote green investing, with emphasis on financial performance and long term viability of companies. It is based upon purely quantitative and objective performance signals to assess carbon performance. Another important example of a thematic index in Indian stock market is the BSE TASIS Shariah50, the first Shariah compliant equity index in India constructed using the strict guidelines and local expertise of a domestic, India-based Shariah advisory board. The BSE TASIS Shariah 50 index consists of the 50 largest and most liquid Shariah compliant stocks within the BSE 500. Thematic indices are gaining popularity in international stock markets also. The MICEX10 Index was launched on March 19, 2001 in the Russian stock market constructed on the 10 most liquid blue chip stocks. Dow Jones U.S. Thematic Market Neutral Anti-Beta Index is another popular thematic index which measures the performance of an investment strategy utilizing short positions on high beta companies and long positions on low beta companies.

This paper focuses on survey of literature available on different techniques of modeling financial time series and application of such techniques to modeling of stock market indices in different stock markets of the world for comparing the efficacy of such techniques in forecasting future movements of stock market indices.

OBJECTIVES OF THE STUDY

The objective of the study are

· Survey of literature on different techniques of modeling financial time series;

· Survey of literature on application of such different techniques as applied to modeling of stock market indices in different stock markets of the world and comparing the efficacy of such techniques in forecasting future movements of the respective stock market indices;

· Identifying the most used and the comparatively lesser used financial time series modeling techniques;

· Exploring the scope of application of novel and comparatively lesser used financial time series modeling techniques; and

· Exploring the scope of application of financial time series modeling techniques, both frequently used ones as well as novel ones, on other indices e.g. sectoral and thematic stock market indices

Literature Survey : Literature Survey for this paper has been done to gather knowledge on the following aspects:

A. Techniques professed by scholars, both traditional and modern, for time series analysis with emphasis on financial time series analysis and modeling from a theoretical standpoint

One of the most important types of data used in econometric analysis is time series data. Time series data, due to their intrinsic nature poses several challenges in analysis and modeling thereof. (Gujrati et al 2012) lists out certain peculiarities in time series data.

· Empirical work on time series data assumes that the underlying time series is stationary which can be in contradiction to reality. Causality tests e.g. Granger and Sims Tests are examples of such assumptions. Thus tests of stationarity should precede the tests of causality in case of time series analysis and modeling;

· There are chances of autocorrelation if the time series is non-stationary;

· While regressing a time series variable, very high values of R^2 (in excess of 0.90) may be obtained in spite of absence of a meaningful relation between the variables i.e spurious regression;

· Some financial time series, specially stock market indices, exhibit a *Random Walk Phenomenon*;

· Validity of regression models on time series data is lost if the time series is not stationary;

There are five methods of forecasting on a time series variable are:

Ø Exponential Smoothing Methods i.e. method of fitting a suitable curve to a historical data of a given time series. Single Exponential Smoothing, Holt's Linear Method and Holt-Winters' Method are variants of the exponential smoothing methods;

Ø Single Equation Regression Models i.e. estimation of an appropriate model of a variable, usually linear or log-linear, which can be used for forecasting future values of that variable. However forecasting errors increase with the increase in futurity of the forecasting involved ;

Ø Simultaneous-Equation Regression Models: these models though popular in the 50s and 60s, faired poorly in forecasting time series data specially after the 1973 and 1979oil crisis (Gujrati et al 2012);

Ø The Autoregressive Integrated Moving Average (ARIMA) method, popularly known as the Box-Jenkins Method i.e. analyzing the stochastic properties of the time series data instead of constructing single equation or simultaneous equation models; and

- Ø The Vector Autoregression (VAR) Method i.e. considering several endogenous variables together where each endogenous variable is explained by its past values with usually no exogenous variable involved

Among the above five models, the last two i.e the ARIMA and VAR models have gained global popularity (Gujrati et al 2012).

Financial Time Series analysis and modeling is primarily associated with the theory and practice of asset valuations and return over time. Tsay (2010) points out the difference between a financial time series and other time series in as much as both financial theory and its empirical time series contain an element of uncertainty. Tsay (2010) cites the example of various definitions of asset volatility and for a time series of stock-return data, volatility is not directly observable. This added uncertainty enhances the role of statistical techniques in analysis and modeling of a financial time series.

Gujrati et al (2012) identifies that financial time series data e.g. prices of financial assets, foreign exchange rates, stock market indices etc. are characterized by volatility clustering i.e certain periods of time when the data exhibit wide swings for an extended time period followed by a period where they exhibit comparative tranquility. The following models can capture such volatility clustering:

- Ø Autoregressive Conditional Heteroscedasticity (ARCH) Model – originally developed by Engle, which focuses on and considers the fact that variances in a financial time series varies over time; and
- Ø Generalized Autoregressive Conditional Heteroscedasticity (GARCH) Model – proposed by Bollerslev which says that the conditional variance at a time is dependant not only on the squared error term in the previous time period (as in ARCH) but also on its conditional variance in the previous time period.

Tsay (2010) proposes the following statistical techniques for analyzing and modeling financial time series data;

- · Linear Time Series Analysis
  - o Simple Autoregressive Models:
  - o Simple Moving-Average Models: It is an infinite-order autoregressive model with some parameter constraints.
  - o Simple Autoregressive Moving Average (ARMA) Models: This is a combination of the concepts of autoregression and moving average which is needed to construct high-order models with many parameters to describe the dynamic structure of the time-series data
  - o Random walk Model for Unit Root Non-Stationarity: Some financial time-series variables e.g. stock market indices, foreign exchange rates, security prices etc. tend to be non-stationary mainly due to the fact that there are no fixed levels for the price. This phenomenon is known as the Unit Root Non-Stationarity and the most popular model to address this type of situation is the random Walk Model.
  - o Seasonal Models: These models address the phenomenon of cyclical or periodic behavior of certain financial time series data e,g, quarterly Earnings Per Share (EPS) of a particular scrip
- · Non-Linear Models
  - o Bilinear Model:
  - o Threshold Autoregressive (TAR) Model
  - o Smooth Transition Autoregressive (STAR) Model
  - o Markov Switching Model
  - o Non-parametric Methods
  - o Functional Coefficient Autoregressive (FCAR) Model
  - o Nonlinear Additive Autoregressive (NAAR) Model
  - o Nonlinear State-Space Model
  - o Neural Networks
- · Conditional Heteroscedastic Models
  - o The ARCH Model
  - o The GARCH Model
  - o The Integrated GARCH (IGARCH) Model
  - o The GARCH-M Model
  - o The Exponential GARCH (EGARCH) Model
  - o The Threshold GARCH (TGARCH) Model

- o The Conditional Heteroscedastic ARMA (CHARMA) Model
- o The Random Coefficient Autoregressive Model
- o The Stochastic Volatility Model
- o The Long-Memory Stochastic Volatility Model
- · Continuous-Time Stochastic Models
- o The Wiener Process
- o Generalized Wiener Process
- o Ito Process
- o Jump Diffusion Models
- · State-Space Model & Kalman Filter
- o Local Trend Model:
- o Linear State-Space Model:
- o Kalman Filter & Smoothing:
- · Markov Chain Monte Carlo (MCMC) Method: The focus here is to create a Markov process whose stationary transition distribution is specified and to run the simulation sufficiently long so that the distribution of the current values is close enough to the stationary transition distribution.
- · Value at Risk (VaR) Model: VaR is principally concerned about market risks though the concept and application of VaR can be extended to other risks also. VaR is a single estimate of the amount by which the investor's position in the risk category could decline due to market movements given a definite period of holding an asset

Scholars like Zellner (1962), Mark et al (2005), Moon & Perron (2006), Parlow (2010), Takada et al (1995) and Yoshimoto (2008) have professed the technique of *Seemingly Unrelated Regression (SUR)* which can be utilized in forecasting a time series.

Another technique of Simultaneous Equation System (SES) can be utilized for the same purpose as put forward by scholars like Haavelmo (1943), Zellner & Palm (1974), Chow (1973), Gallegati & Ramsey (2009) and Gao & Philips (2012).

B. Techniques applied by scholars for analysis and modeling of financial time series with emphasis on various stock market indices across the globe with findings thereof

Literature survey on this aspect reflects a heavy tilt in favour of the techniques of Neural Networks, Fuzzy Logic, ARMA/ARIMA and ARCH/GARCH models. Comparatively lesser weight have been given to methods like VaR, State Space formulations, Multifractal Detrended Fluctuation Analysis, Markov Chains, Extreme Quantile Tracking, Seemingly Unrelated Regression, Simultaneous Equation System and Support Vector Techniques.

Studies involving Neural Network Technique

Aamodt (2010) found out that long term models outperformed the short term models. On an overall basis the model was unable to handle the turmoil in the stock market. Moreover, numerous variable need to be configured in finding a good set of settings for each neural network. This becomes an overwhelming task in itself. Khan (2011), Pissarenco (2002), Krollner (2010), Kutsurelis (1998), Hajizadeh (2010) and Hajek (2012) also utilized the technique of neural network in modeling financial time series with satisfactory results. This technique was found to be reasonably accurate in predicting stock market movements by Babu (2011) who studied the Indian stock market and also by Panahian (2011) who studied the capital market of Iran. Kumar (2009) found this technique to be suitable in his study on S&P 500 & Hang Seng Indices. Singh (2009) found the neural network technique to be a promising tool for forecasting financial time series. Studies on Tehran stock market by Aghababaeyan and on Turkey stock market by Egeli also yielded reliable results by neural network method. Hsu (2010) used Self Organizing map (SOM) technique, a modified form of neural network to satisfactory effects. Flores used a hybrid neural-evolutive approach and found the results to outperform those obtained by ARIMA model by working on data from Banco de Mexico. Dablemont & Verleysen (2005), on the basis of their study, opined that This method can be applied to all types of time series but is particularly effective when the observations are sparse, irregularly spaced, occur at different time points for each curve, or when only fragments of the curves are observed. Standard methods were found to be completely failing in these circumstances as observed by them.

Studies involving ARCH / GARCH / EGARCH Techniques

Kunst (1997) found ARCH model to be effective. Scholars like Claessen & Mittnick (2002) studied the DAX Index Option market and found the GARCH model to be suitable. Similar observations were put forward by Frances & Dijk (1996), Lobato et al (2007), Mikosch & Starica (2004) and Gherman et al (2012) on the basis of their respective studies. Yang (2012) also shared similar views on the basis of the study on Taiwan Stock Market. Koutmos (2004) found the

EGARCH model to be effective in modeling financial time series. Bauer (1994) found both the methods of ARCH & GARCH to be useful in modeling the German Stock market. Ladokhin (2009) used ARCH and GARCH techniques along with neural networks to model financial time series. Princ (2011) used a combination of ARMA & GARCH models. Malmsten (2004) found the ARCH & GARCH models useful while Zhuang (2004) found the combination of GARCH model and Hidded Markov Model effective in modeling financial time series. Zhang (2001) also found the Hidden Markov Model to be effective in modeling financial time series.

Studies involving ARMA/ARIMA models

Among scholars who found ARMA model effective are Fuh (2003), Thalassinos and Tolvi (2002) who did a study on OECD countries. The ARIMA model was found to be preferred by Leung et al (2000). Preethi and Santhi (2012) also share the same view. They further state that, neural network results are unstable. The neural network functions are Block Box functions. The rules of operations are completely unknown. Moreover back propagation networks can be take long time to train the large amount of data. They further stated that unlike a regression model, ARIMA model does not support the stationary time series data. Kumar (2009) also found the ARIMA model useful in predicting foreign exchange rates from stock market data. Oomen (2001) carried out a comparative study and inferred that ARFIMA outperforms GARCH in forecasting but simplicity and flexibility of GARCH is better.

Studies involving Fuzzy Logic Techniques

Among scholars who found fuzzy logic models effective in modeling financial time series are Chu (2009) who studied the TAIEX and NASDAQ data, Souto-Maior (2011) who studied the S&P 500 data, Chen (2011) who studied the Taiwan Stock Market and Aznarte (2012) who studied the Dow Jones Industrial Average (DJIA) Index.

Studies involving Non-Linear Techniques

Clements et al (2003) tried non-linear models in modeling financial time series and opined that application of existing techniques, and new models and tests, can result in significant advances in understanding financial time series. Assuming that the world is inherently non-linear, then with increasing computational capabilities, more complex models become amenable to analysis, allowing the possibility that future models will outperform linear models, especially if such models become multivariate. Lendasse (2000) did a study on Bel 20 Stock market index using non-linear models with reliable results.

Studies involving other techniques

Chow (1973) did a study on Sanghai and New York Stock Exchanges using simple autoregression with Granger causality tests with reliable results. Zhang & Zhang (2009) used the Markov Chain in modeling financial time series. Agwuebo (2011) modeled the Nigerian Stock Market using State Space Formulation with Kalman Filter. The Kalman filter technique is adopted in this study as the best linear filter in an expected square error sense, and the filter algorithm degenerates into simpler algorithm that is identical with the conventional time series method of forecasting. Kalman filter has been found to be useful by Dablemont et al and Gupta et al (2005). Azzaouzi used Switching State Space Models and found then to be more powerful probabilistic models for modeling time series. Their application in modeling financial time series is new. Chavez-Demoulin resorted to Extreme Quantile Tracking in modeling time series. Snguanyat (2009) used the Multifractal Detrended Fluctuation Analysis (MF-DFA) with satisfactory robustness. Kim (2003) and Kumar, in their respective studies, found Support Vector Machines to be a superior technique in modeling financial time series. Lu (2009) also opined that Support Vector Regression is an effective method for regressing financial time series data. Guermat et al (2003) modeled the Arab Stock market using value At Risk VaR model with satisfactory results. Jung & Boyd (1996) found similar reliable results by modeling the UK stock market using VaR techniques.

FINDINGS

The literature survey reveals that the study on financial time series analysis and modeling have been carried out by scholars who have principally relied upon techniques like Neural Networks, ARCH/GARCH/EGARCH, Fuzzy Logic and VaR. Other useful techniques, which have been empirically tested to be capable of building robust models e.g. Multifractal Detrended Fluctuation Analysis, Support Vector Techniques etc. have been less used. This study also reveals that different techniques have been proved to have different forecasting accuracy on different sets of time series data. Thus no method for modeling financial time series data has been unanimously proved to be the best by maintaining better forecasting ability withstanding the variation in time periods and data sets. Methods like Seemingly Unrelated Regression and Simultaneous Equation System have not been applied in the research papers studied for this paper. Moreover, the modeling of financial time series in all the papers studied, have been done on broad based indices only. This leaves a gap in testing the applicability of financial time series modeling in sectoral and thematic stock indices which are actively followed in capital markets the world over.

CONCLUSION

The suitability of financial time series modeling techniques on various time series data, more particularly, stock market indices, possess considerable dynamism. In addition, The manner and degree of the effect of macro-economic variables and investor psychology on broad based indices are different from that on sectoral and thematic indices. Besides sectoral indices which track the movement of stock prices of organizations belonging to a particular sector, thematic indices e.g. BSE Greenex, BSE Carbonex and BSE Shariah 50 in Indian stock market, are also gaining popularity. The degree to which these indices lend themselves to financial time series modeling, needs to be explored. The recent recession has left the stock markets all over the world exhibiting unexpected swings. The applicability of different time series modeling techniques should be tested on different stock market indices over different periods of time to have a better understanding of movement of the different indices. This in turn would assist the investors and portfolio managers to enhance their returns on investment as also to hedge against future uncertainties in a better manner.

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