ISSN (Online): 2230-7893
www.IJCEM.org

Use of Parametric and Non-Parametric Techs. for Stock Market Volatility: A Survey

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Abstract
Since the 1960's there have emerged numerous studies questioning the degree of stock market efficiency. Fields like behavioral-economics, Finance & Computational finance have received much attention for their more flexible & detailed view regarding the volatility of stock markets in the emerging as well as in the development economics .Soft computing approach (Artificial Neural Network: ANN) has been applied to a number of systems in Financial Engineering & in many cases has demonstrated better performance than competing approach. This study is a survey on Parametric and Non- Parametric approaches to investigate the extent of these applications and to document the manner in which the ANN technologies specifically are implemented in stock market.

Keywords: GARCH, EGARCH, IGARCH, TGARCH, ANNS

Introduction:

The financial markets around the global play an important role in the process of economic growth and developments by facilitating savings and channeling funds from savers to investors. While there have been numerous attempts to develop the financial sector, small as well as emerging economies face the difficulty of high volatility and low liquidity in numerous fronts including the volatility of its financial markets. Volatility and illiquidity may impair the smooth functioning of the financial system and adversely affect economic performance. Stock market volatility has negative implications on the industrial growth of a country. One of the ways in which it affects the economy is through its effect on consumer spending.

Stock market volatility may also affect business investment and economic growth While there is a general consensus on what constitutes stock market volatility, and, to a lesser extent, on how to measure it, there is far less agreement on the causes of changes in stock market volatility. The cause of volatility is the arrival of new and unanticipated random information (Engle and Ng, 1993). Thus, changes in market volatility would merely reflect changes in the national or global economic environment. Others claim that volatility is caused mainly by changes in trading volume, modification in macroeconomic policies, shifts in investor tolerance of risk and increased uncertainty. The degree of stock market volatility can help forecasters predict the path of an economy's growth and the structure of volatility can imply that 'investors now need to hold more stocks in their portfolio to achieve diversification.

During the 20th as well as in 21st century, the emerging economies have been taking measures for bringing reforms and developments in order to deepen their financial sectors. Unlike mature stock markets of advanced economies, the stock markets of emerging economies are not only sensitive to the changes in the level of economic & political activities but also to the changes in economic environment of national and international level and macro economic variables.

As volatilities play a very important role in finance area and accurate estimation of volatilities is key to e.g. risk management and derivatives pricing, this paper tried to sum up the applications of Parametric & Non Parametric (Different approaches of Artificial Neural networks) for calculating it.

Parametric Approach:

The Parametric approaches include the seminal works of Engle (1982), on the ARCH model and its generalized form (GARCH) by Bollerslev (1986) to calculate the volatilites of Stock market. The extension of GARCH models were used by French, Scwart and Stambaugh (1987); Akgiray (1989); Ballie and DeGennaro (1990); Lamoureux and Lastrapes (1990); Corhay and Tourani (1994); Geyer (1994); Nicholls and Touri (1995).

Also Zuliu Hu (1995) examined whether the stock market volatility affects real fixed investment. The empirical evidence obtained from the US data shows that market volatility has independent effects on investment over and above that of stock returns. Volatility and its changes are negatively related to investment growth. To the extent volatility depresses fixed capital formation and hence future income growth; the results suggest the desirability of reducing stock market volatility.

Yeliz Yalcin, Eray M. Yucel (1997) investigated day-of-the-week (DOW) anomalies in the stock markets of twenty emerging economies. They used a modified exponential generalized autoregressive conditional heteroskedasticity in-mean (EGARCH-M) modeling strategy that allows for the simultaneous examination of DOW effects on market return and variability. Here, also DOW effects are present in market returns for only three countries, in market volatility for only five countries, and they are present in both for only one country, when the estimates are evaluated at the 1 percent significance level. Despite this, at lower levels of significance the common qualitative patterns in the estimates are extracted such that the higher returns are concentrated around Fridays, whereas volatility is highest on Mondays and lowest on Tuesdays and Friday.

Nicholas Apergis and Sophia Eleptheriou (2000) investigated the volatility of the Athens Stock market's stock returns over the period 1990-1999 through the comparison of various conditional hetero-skedasticity models. The empirical results indicated that there is significant evidence for asymmetry in stock returns, which is captured by a quadratic GARCH specification model, while there is strong persistence of shocks into volatility.

Shyh-Wei Chen Chung-Hua Shen (2004) paper investigated the common volatility structure of stock and exchange rate for the markets of Taiwan . They found that common volatility does exist in the stock and exchange markets and this fact is uncovered more easily by using trading volume than by using prices. Efficient Market Hypothesis (EMH) has attracted a considerable number of studies in empirical finance, particularly in determining the market efficiency of an emerging financial market. Conflicting and inconclusive outcomes have been generated by various existing studies in EMH. In addition, efficiency tests in the emerging financial markets are rarely definitive in reaching a conclusion about the issue.

Sardar M.N. Islam, Sethapong Watanapalachaikul and Colin Clark (2005) proposed a theory-free paradigm of non-parametric tests of market efficiency for Thai stock market, consisting of two tests which are run-test and autocorrelation function tests (ACF), to establish a more definitive conclusion about EMH in emerging financial markets. The result of this research demonstrates that an autocorrelation on Thai stock market returns exists particularly during the post-crisis period. The inefficiency of the Thai stock market follows on from the violation of the necessary conditions for an efficient market with a developed financial system and also implies financial and institutional imperfections

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Mala Rajni, Reddy Mahendra, (2006) used the Autoregressive Conditional Heteroskedasticity (ARCH) models and its extension, the Generalized ARCH, GARCH model was used to find out the presence of the stock market volatility on Fiji's stock market. . The analysis was done using a time series data for the period 2001- 2005 on specific firms and it was found out that seven out of the sixteen firms listed on Fiji's stock market is volatile. The volatility of stock returns were then regressed against the interest rates and the results showed that the interest rates changes have a significant effect on stock market volatility

Haitham Al-Zoubi, Bashir Kh. Al-Zu'bi (2007) examined the market efficiency, asymmetric effect and time varying risk-return relationship for daily stock return of Amman Stock Exchange (ASE)using Box-Jenkins,EGARCH,TGARCH.

Samanta Pretimaya and Samanta Pradeepta K. (2007) used the standard univaraite. GARCH model to capture the time-varying nature of volatility and volatility clustering phenomenon in the data (S & P CNX Nifty, Nifty junior, and S & P 500 index from October 4, 1995 to December 31, 2006). The evidence suggests that there is no significant change in the volatility of the spot market of the S & P CNX Nifty index, but the structure of the volatility has changed to some extent. However, some interesting results in case of introduction of stock futures suggest that it has moved results in spot market volatility in the case of tend individuals stocks.

Yu Wei_, Peng Wang, (2008) shows the forecasting accuracy of volatility of SSEC in Chinese stock market using MFV (multifractral volatility). In this paper, taking about 7 years' high-frequency data of the Shanghai Stock Exchange Composite Index (SSEC) as an example, the authors proposed a daily volatility measure based on the multifractal spectrum of the high-frequency price variability within a trading day. An ARFIMA model is used to depict the dynamics of this multifractal volatility (MFV) measures. The one-day ahead volatility forecasting performances of the MFV model and some other existing volatility models, such as the realized volatility model, stochastic volatility model and GARCH, are evaluated by the superior prediction ability (SPA) test. The empirical results show that under several loss functions, the MFV model obtains the best forecasting accuracy.

Chiao-Yi Chang (2009) explores the evidence of asymmetric volatility clustering in emerging stock market taking Taiwan comparing to US. Using TAR-GARCH model, his results find that the strength of volatility clustering are related to the negative serial correlation in emerging stock market, but not positive serial correlation.

Non -Parametric Approach:

In this modern age, Soft computing approach (Artificial Neural Network: ANN) has been applied to a number of systems in Financial Engineering & in many cases has demonstrated better performance than competing approach. The purpose of study in this section is to investigate the extent of these applications and to document the manner in which the ANN technologies are implemented in stock market**.**

White (1988) was the first to use neural networks (NNs) for market forecasting. He was curious as to whether NNs could be used to extract nonlinear regularities from economic time series, and thereby decode previously undetected regularities in asset price movements, such as fluctuations of common stock prices. The purpose of his paper was to illustrate how the search for such regularities using a feed-forward NN (FFNN) might proceed, using the case of IBM daily common stock returns as an example. White found that his training results were overoptimistic, being the result of over-fitting or of learning evanescent features. He concluded, "the present neural network is not a money machine.

Yoon and Swales (1990) compare neural networks to discriminant analysis with respect to prediction of stock price performance and find that neural network is superior to discriminant analysis in its predictions. Hertz,Krogh and Palmer (1991) offer a comprehensive view of Neural Networks and issues of their comparison to statistics. Also Hinton (1992) investigates the statistical aspects of Neural Networks.

Chiang et. al. (1996) used a FFNN with backpropagation (BP) to forecast the end-of-year net asset value (NAV) of mutual funds, where the latter was predicted using historical economic information. They compared those results with results obtained using traditional econometric techniques and concluded that NNs "significantly outperform regression models" when limited data is available

Kuo et. al. (1996), recognized that qualitative factors, like political effects, always play a very important role in the stock market environment, and proposed an intelligent stock market forecasting system that incorporates both quantitative and qualitative factors. This was accomplished by integrating a NN and a fuzzy Delphi model; the former was used for quantitative analysis and decision integration, while the later formed the basis of the qualitative model. They applied their system to the Taiwan stock market

Karaali, O.,Edelberg, W.Higgins, J. Motorola Inc., Schaumburg, IL, (1997) evaluate the index's time series properties, explore a closed-form solution for valuing derivative instruments based on the index, and employ neural network methods to price options based on the index. Lastly, they explore a practical example of using futures on the index to hedge the volatility risk of a portfolio of Deutschemark options.

Kim, S. H. and S. H. Chun. (1998): Kim and Chun (1998) used a refined probabilistic NN (PNN), called an arrayed probabilistic network (APN), to predict a stock market index. They concluded that the APN tended to outperform recurrent and BP networks, but that case base reasoning tended to outperform all the networks.

Thammano, A. (1999) concluded that the neuro-fuzzy architecture was able to recognize the general characteristics of the stock market faster and more accurately than the basic backpropagation algorithm. Also, it could predict investment opportunities during the economic crisis when statistical approaches did not yield satisfactory results.

Trafalis (1999) used FFNNs with BP and the weekly changes in 14 indicators to forecast the change in the S&P 500 stock index during the subsequent week They found that linear optimization methods gave the best estimates, although the GAs could provide the same values if the boundaries of the parameters and the resolution were selected appropriately, but that the NNs resulted in the worst estimations. However, they noted that nonlinearity could be accommodated by both the GAs and the NNs and that the latter required minimal theoretical background.

Garliauskas (1999) investigated stock market time series forecasting using a NN computational algorithm linked with the kernel function approach and the recursive prediction error method. He concluded that financial times series forecasts by the NNs were superior to classical statistical and other methods.

Kim, K-J. and I. Han.(2000) used a NN modified by a GA to predict the stock price index. They concluded that the GA approach outperformed the conventional models. Moshou D.Ramon H.(2000) also used Wavelets and self-organizing maps in financial time series analysis. Abraham,

A., B. Nath and P. K. Mahanti.(2001) investigated hybridized SC techniques for automated stock market forecasting and trend analysis. They used principal component analysis to preprocess the input data, a NN for one-day-ahead stock forecasting and a neuro-fuzzy system for analyzing the trend of the predicted stock values. They concluded that the forecasting and trend prediction results using the proposed hybrid system were promising and warranted further research and analysis.

Cao, L. and F. E. H. Tay,(2001) used Support Vector Machines (SVMs) to study the S&P 500 daily price index. The generalization error with respect to the free parameters of SVMs were investigated and found to have little impact on the solution. They concluded that it is advantageous to apply SVMs to forecast the financial time series.

Hwarng (2001) investigated NN forecasting of time series with ARMA (p,q) structures. He concluded that FFNN with BP generally performed well and consistently for time series corresponding to ARMA(p,q) structures.

Sfetsos A.(2002) discussed the application of Neural Logic Networks in time series forecasting.This paper examines their prospect in forecasting of time series and compares their performance with linear models and the Feed Forward Neural Network. Additionally, the suitability of logic rules, generated from a Neural Logic Network, as potential inputs to forecasting systems is also examined. They are applied on two different meteorological series with strong features: a mean hourly wind speed series that exhibits behavior similar to random walk and an hourly solar radiation series selected because of its seasonal nature with discontinuities

Kim Kyoung-Jae, Boo Lee (2004) compares a feature transformation method using a genetic algorithm (GA) with two conventional methods for artificial neural networks (ANNs) *also the GA is incorporated* to improve the learning and generalizability of ANNs for stock market prediction. Their experimental results show that the proposed approach reduces the dimensionality of the feature space and decreases irrelevant factors for stock market prediction

Michalak K., Lipinski P. (2005) discusses the abilities of neural networks to learn and to forecast price quotations as well as proposes a neural approach to the future stock price prediction and detection of high increases or high decreases in stock prices. Sohn S. Y, Shin H. W. (2005) propose a new approach where the forecasting results of GARCH and neural networks are combined based on the weight reflecting the inverse of EWMA of the mean absolute percentage error (MAPE) of each individual prediction model. Empirical study results indicate that the proposed combining method has better accuracy than GARCH, neural networks, and traditional combining methods that utilize the MAPE for the weight.Cao L., Jingqing Z.(2005) shows that the SVMs mixture achieves significant improvement in the generalization performance in comparison with the single SVMs model. In addition, the SVMs mixture also converges faster and use fewer support vectors for time series forecasting. .

De Leone R., Marchitto E., Quaranta A. G. (2006) tried to derive accurate forecasting result considering the future behavior of the market in order to identificate the so-called "correct timing".They also analyze three different approaches for forecasting financial data: Autoregression, artificial neural networks and support vector machines to determine potentials and limits of these methods considering the Italian financial market

Al-Qaheri H., Hassanien A. E., Abraham A. (2008) presents a generic stock pricing prediction model based on a rough set approach. In his paper the results obtained using the rough set approach were compared to that of the neural networks algorithm and it was shown that the Rough set approach has a higher overall accuracy rate and generates more compact and fewer rules than the neural networks.

Majhi R, Panda G, Majhi B., Sahoo G., (2009) introduces the use of BFO and ABFO techniques to develop an efficient forecasting model for prediction of various stock indices. They observed that the new models are computationally more efficient, prediction wise more accurate and show faster convergence compared to other evolutionary computing models such as GA and PSO based models.

The study of J.K.Mantri et al(2010). shows the applications of different methods i.e GARCH, EGARCH, GJR- GARCH, IGARCH & ANN models for calculating the volatilities using fourteen years of data of BSE Sensex & NSE Nifty. The performance of data exhibits that, there is no difference in the volatilities of Sensex, & Nifty estimated under the GARCH, EGARCH, GJR- GARCH, IGARCH & ANN models

Conclusion:

This paper surveyed on the parametric and nonparametric approaches (especially Artificial Neural network) for calculating the volatilities of stock market. We conclude that ANNs has ability to extract useful information from large set of data therefore ANNs play very important role in stock market prediction and also ANNs are significantly more accurate than other competitive models and algorithm, multiple linear regression analysis models for stock market prediction and volatilities. In future Artificial Neural Network with NLP (Natural language processing & Fuzzy logic) can also be helpful to estimate the accurate volatilities and prediction of stock market this Modern Age

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