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FORECASTING EQUITY INDEX VOLATILITY: EMPIRICAL EVIDENCE FROM JAPAN, UK AND USA DATA

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ABSTRACT

Using non-linear models to forecast volatility for three equity index samples, this study examines weekly returns of three indices; Dow Jones Industrial index, FTSE 100 index, and Nikkei 225 index. The sample covers a twenty year sample period. The study employs an in sample and out of sample volatility forecast using standard symmetric loss functions in order to identify an appropriate model that best forecast volatility. Using the mean error (ME), root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE), the study finds the EGARCH model to outperform the ARCH, and GARCH model in forecasting volatility.

Contribution/Originality: This is among the first studies that found EGARCH model to outperform the ARCH, and GARCH model in forecasting volatility using a combination of Japan, UK and US data.

1. INTRODUCTION

Modelling and forecasting volatility has been the subject of most economists, financial experts, researchers, financial advisors and economic policy makers over the past three decades (Boguth *et al.*, 2011; Constantinides *et al.*, 2013; Bollerslev *et al.*, 2016; Cipollini *et al.*, 2017; Bollerslev *et al.*, 2018). Volatility forecasting plays a vital role in the black and Scholes (BS) option pricing theory, providing key function in pricing options in the financial market. In the Black and Scholes (BS) model, four parameters are observable in this model, with volatility being the only parameter that is unobservable. This has given Derivative traders and financial dealers difficulties as to how to observe or predict this parameter accurately. Regulators, Practioners and Academics have embraced Value at Risk and many view Value at Risk as a vital component of current best practice in risk management. One of the most common methods of parametric approach in Value at risk requires calculating the volatility of a return series.

In this work, we explore a number of models ranging from the linear models to the more sophisticated nonlinear models, on weekly volatility of three equity index from three different indices and they include; the Dow Jones Industrial index, FTSE 100 index and the Nikkei 225 index. The mean square error (MSE), root mean square error (RMSE), mean absolute percentage error (MAPE) and the mean absolute error (MAE) will be employed later in this work to evaluate the performance of the various models as to how they forecast volatility.

Why Study Volatility?

Volatility plays a crucial role in financial markets and hence it is important to understand this concept, which is why we model volatility using the non-linear models in this work. Volatility quantifies risk and thus plays a major role in modern finance. Black and Scholes (1973) evaluated volatility using the option pricing formula. It shows the relationship between an option's price and several other factors, including volatility of the underlying asset's price.

Ye-Hsiang (1993) argued that in order to derive an option's price from the Black and Scholes formula, the option is replicated by a portfolio consisting of the underlying asset and a risk free bond. In the Black and Scholes formula, different expectation of volatility will result in a different option price from this formula. This allows for an arbitrage opportunity if the option's market price is different from the initial cost of the portfolio. Thus an option trader is able to make profit by making superior forecasts of future volatility. With the vast portion of the financial markets so dependent on the volatility behaviour, there are obvious benefits to understanding volatility better. Improved forecast would allow traders to price their options more accurately. Using more frequent data provide better estimation of volatility.

Day and Lewis (1992) proved that volatility can be predictable using the ARCH models and that volatility is entirely captured by implied volatility within the Black and Scholes model. The reason for this is that Autoregressive models are still not entirely exploited by the market. However, Kuwahara and Marsh (1992) argued that the conditional volatility derived from GARCH and EGARCH models enable researchers to obtain option values which are very close to those that could be observed by the market. This suggests that conditional volatility cannot be used as an additional source of information, since it can be observed in the implied values. According to Michael Minnich, vice president of capital market risk advisor, Value at risk is a very important component of risk management and also an important part of volatility forecasting.

Furthermore, modelling and forecasting volatility has been subject of interest to many academicians, portfolio analysis's and those involved with risk management. There has been growing interest in this area of research as a result of the current economic crisis hitting most countries of the world. The indices of most countries are experiencing severe downturn and hence derivative traders, academicians and portfolio managers are more concern about this problem. The purpose of this paper then is to forecast volatility using the non-linear models and applying the various standard symmetric loss functions to evaluate which of these models forecast volatility better.

The rest of the paper is structured as follows: section 2 presents a concise review of the various literature on volatility. Section 3 discusses the methodology while section 4 and 5 is analyses the empirical results and conclusion respectively.

2. LITERATURE REVIEW

Over the last two decades, there has been an increasing interest in modelling the volatility of stock market returns (Akgiray, 1989; Dimson and Marsh, 1990; Pagan and Schwert, 1990; Boguth *et al.*, 2011; Constantinides *et al.*, 2013; Bollerslev *et al.*, 2016; Cipollini *et al.*, 2017; Bollerslev *et al.*, 2018). This is basically due to the highly volatile movements of prices of stock returns in the financial market. This has led researchers into investigating the level and stationarity of volatility over time (Day and Lewis, 1992; Tse and Tung, 1992; Figlewski *et al.*, 1993). Most research has been directed towards examining the accuracy of this forecast. Both linear and nonlinear models have been applied by different researchers and each of them came out with different conclusions as regards the accuracy of volatility forecast (Cao and Tsay, 1992; Heynen and Kat, 1994; Brailsford and Faff, 1996; Figlewski, 1997).