ON FORECASTING STOCK OPTIONS VOLATILITY: EVIDENCE FROM LONDON INTERNATIONAL FINANCIAL FUTURES AND OPTIONS EXCHANGE

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Abstract:
Options' volatility forecasting represented, in the last decades, a very interesting and frequent domain of research in financial econometrics due to its importance in option pricing, portfolio selection, risk management and other financial activities. The aim of this study is to realize a comparative analysis of the performances obtained by several forecast models in forecasting stock options volatility.
For this, we consider the volatility of the 4 most traded options at Euronext London International Financial Futures and Options Stock Exchange (Euronext.Liffe) in the period 2009-2010.
When analyzing and forecasting these stock options we use the period January 2009-May 2011; using this base period, we determine the models that describe better the evolution of the volatility. Based on these models we realize forecasts that are finally compared with the real values recorded in the next 10 trading days.
In relation with the differences that appear, we determine the forecast errors and by these we identify the best models and the ones that generate the biggest errors.

Key words: *options, volatility, forecast, EWMA, GARCH class models*

JEL classification: G17

1. INTRODUCTION

Starting with the introduction of the Black-Scholes model (1969) and with the creation of the first options stock exchange – Chicago Board of Options Exchange in 1973, the options theory had a very dynamic evolution, in both innovation and theoretical fundament.

Used as well for covering risk but also for getting better financial performances, options can be found in the portfolios of all kind of investors.

Options' price, as well as its' underlying asset price are affected by a strong random component. Their predictability depends on sure events but mostly on random events. The development of the financial medium generates higher risks that are more and more expensive to cover. That is why the risk exposure of any company must incorporate also its own appreciation regarding the possible loss that may appear (Hull, 2008).

Studying the financial market volatility is an issue of major interest for public authorities with responsibilities in ensuring financial stability and also theorists and practitioners in financial markets. The term volatility is synonymous, for specialists, with the phenomenon of risk: high volatility causes panic among investors, with negative effects on the stability of financial markets (Gregoriou, 2009).

Options' volatility forecast has represented, in the last decades, a field of interest for specialists all over the world. A proof for this is the fact that many econometric models for forecasting volatility have been developed and published in books, articles and studies.

In this register, we propose a study regarding 4 most traded stock options traded at Euronext London International Financial Futures and Options Exchange

(Euronext.Liffe) in the period 2009-2010. We analyze the evolution of these 4 options in the base period of January 2009-May 2011 and using the models the describe best this evolution, we realize forecasts that are finally compared with the real values recorded in the next 10 trading days.

After this, we compare the differences that appear between the forecasted values for 1, 5 and 10 days and the real recorded values in the same period; by analyzing these forecast errors, we identify the best models and the ones that generate the biggest errors.

2. LITERATURE REVIEW

Technically speaking, analyzing and forecasting options' volatility means modeling a time series and then, using the found best fitted models, forecasting future values. The literature regarding the time series analyze highlights 2 concepts, namely classical and modern time series analysis.

From this point of view, the results communicated by the literature, identify examples in which the classical time series forecasts have better results and ones that confirm that modern time series methodology offer smaller errors; the most significant part of the literature cannot conclude into saying that there is such thing as the best model in forecast volatility.

A milestone when reviewing volatility forecast literature is the meta-analysis done by Poon (2005); in this study the author makes a survey over 93 articles written in a large period of time regarding volatility forecast. Authors' conclusions join many other articles that conclude that, by that moment, there is no such model that can be considerate the best one.

Taylor (1987) is one of the first to test the historical volatility models performances. He used extreme values (minimum, maximum and closing price) to make 20-day forecast of futures derivatives exchange rate DEM / USD. Models such as random walk or moving average may seem to be very naive nowadays, especially in light of the fact that computing power and data availability increased, but 20 years ago were used, even with success in forecasting.

Sill (1993) shows that S&P500 index volatility is higher during recession time and that the evolution of the USA t-bills determines stock volatility.

Alford and Boatsman (1995) analyzed a set of 6879 stocks and recommended, when investing in a 5 year plan, the estimation of the returns based on weekly and monthly volatility, doing an adjustment relative to the activity field of the company. Cumby, Figlewski and Hasbrouck work and weekly data regarding stock forecast and find that EGARCH is better than naive in forecasting volatility.

Figlewski (1997) analyzed the S&P500 volatility, the short and long term interest in U.S. and DEM / USD exchange rate. Mcmillian Speigh and Gwilym (2000) identify GARCH models to have better performances, while ARCH offers better predictability for Braisford and Faff (1996). Also Ederington and Guan (2006) compare the forecast performances of some volatility models and offer the conclusions that GARCH generally yields better forecasts than the historical standard deviation and exponentially weighted moving average models.

Awartani and Corradi (2005) analyze the errors given by some GARCH models and find that GARCH generates bigger errors than asymmetric GARCH models.

Tse (1991) and Tse and Tung (1992) conclude, when using data from Japan and Singapore, that the model ”exponentially weighted moving average” (EWMA) offer better forecast than ARCH type models and by this putting into questions the superiority of these models, in opposition with Roh (2007) that proves on Korean index KOSPI that EGARCH is better than GARCH and EWMA.

By analyzing an significant amount of the literature, not only the ones cited here, we can say that the right characterization of the literature is of a framework composed by a heterogeneous set of results and we concur too at this point of view.

3. DATA AND METHODOLOGY

Because the aim of the study is to realize forecasts of the volatility for more time horizons, we took into consideration the most 4 traded stock options at Euronext.Liffe. This stock exchange is a part of the first global stock exchange group – NYSE EURONEXT, a very important entity in the framework of financial trading worldwide. Its base is found in 2007, the merger between american NYSE Stock Exchange and the Stock Exchanges from Amsterdam, Londra, Lisbon, Bruxelles and Paris, known by that time as Euronext N.V. group.

Based on annual data supplied by Euronext, we consider 4 most traded stock options from the point of view of traded value. In table no. 1 are presented the most traded stock options in 2009 and 2010 at Euronext. Liffe.

Table no. 1. *Most trade stock options at Euronext.Liffe in 2009 and 2010*

Stock options	**Total traded amount in 2009-2010 (000 EUR)**
Rio Tinto	11340753.400
British Petroleum	7083606.671
BHP Billiton	5786233.343
AstraZeneca	5622496.691
Anglo American	4433006.641
HSBC Holdings	3975480.274
Xstrata	3805257.410
Barclays	3613967.825

Source: Euronext.Liffe

Based on the total traded amount, we propose to analyze the volatility the options written on the stocks of Rio Tinto, British Petroleum, BHP Billinton and Astra Zeneca. For these 4 options we use daily volatility in the period 1 January 2009 - 17 May 2001 (619 trading days) and we determine models for the estimating the volatility; based on these models, we realize forecasts for a time horizon of 10 trading days and then we compare the forecasted values with the recorded values in the period 18 May 2011 – 31 May 2011. Based on these differences, we determine the forecast errors for every model and then we rank the models.

When searching the needed data, we take into consideration Beckers (1981) that says that in this type of analysis we should use data regarding American CALL options. American CALL options entitle the buyer to exercise or abandon the contract at any time until expiration. For 2009-2010, between 97% and 99% of the considered traded stock options were American. Data was retrieved from Thomson Datastream and it represents daily volatility of American CALL options for the 4 stock options traded in this period; their value is being calculated based on binomial Cox-Rubinstein algorithm. We used Eviews 7.2 in doing the estimations.

The estimations were done, for the modern time series analysis, according to Box-Jenkins methodology (1970) in which firstly, the stationary of the time series in checked by means of Augmented Dickey-Fuller test. After the needed transformations, if the series is not stationary, we analyze the corellogram of the series and by the information provided by this we test different ARMA models (Pindyck and Rubienfield, 1998). From the estimated models that are valid, we choose the one in which the indicators based on information theory, namely Akaike (AIC), Schwartz (SC) and Hannan-Quinn (HQC) have the smallest values (Mills and Markellos, 2008).

The chosen model is test for the hypothesis regarding residuals correlation, homoscedasticity test and the normality of the residuals. In all the cases that we did in this paper only the homoscedasticity hypothesis was rejected and that meant that we had to use heteroscedastic models to model the variance – ARCH-GARCH family models. After checking the hypothesis on these models, we realized forecasts.

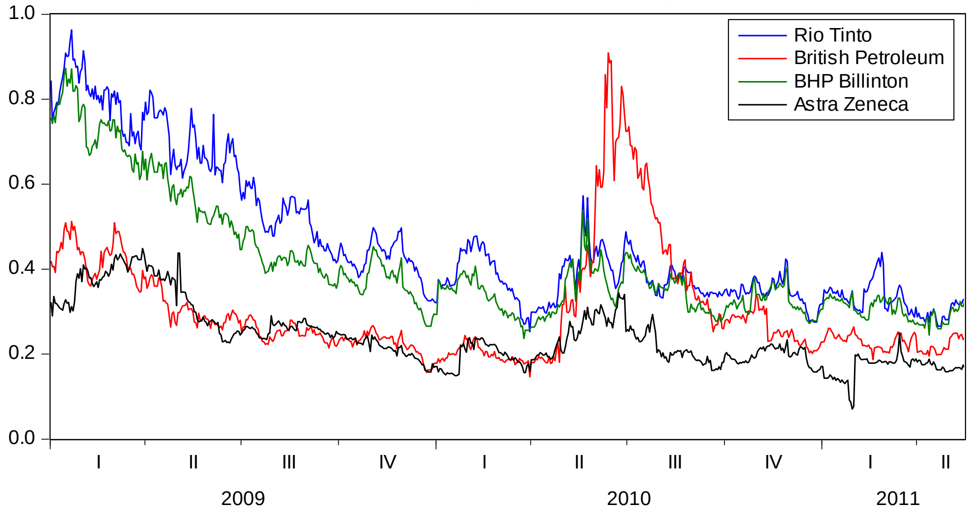
For the chosen classical model, EWMA, there was no hypothesis to check, we just had to make the forecast. We used J.P. Morgan methodology and according to this we considered weighting factor $\lambda=0.94$.

After we have the forecasted values, we compute the forecast errors by comparing these with the real recorded ones. Through out these errors, we rank the used models for 3 time horizon: 1 day, 5 day and 10 day forecasts. In this analysis we use Theil U1 and U2 indicators (Theil, 1966) and the results of LINEX function with the parameters of penalty -20, -10, 10 and 20. These indicators and these were chosen according the literature (Granger, 1999).

4. EMPIRICAL FINDINGS WHEN FORECASTING OPTIONS VOLATILITY TRADED AT EURONEXT.LIFfE

The evolution of the volatility for the 4 options considered is presented in figure no.1.

Figure no. 1 . *Daily volatility of Rio Tinto, British Petroleum, BHP Billinton and Astra Zeneca stock options between 1 Januaty 2009 and 17 May 2011*



Souce: Authors processing after data from Thomson Datastream

In the evolution of the volatility of the 4 stock options we observe high volatility at the beginning of 2009, due to the turbulences on the financial markets, but also for British Petroleum we see high volatility in 2010, probably related to the oil spill over the Golf of Mexico.

After analyzing the time series, we found some autoregressive moving average models (ARMA) completed by heteroscedastic models that were validated and able to explain the evolution of the volatility in the considered period. These are presented in table no. 2.

Table no. 2. *Validated models for estimation of the volatility*

Stock Option	Autoregressive moving average model used	Heteroscedastic model used
Rio Tinto	AR(1) AR (14) MA(1) MA(2)	ARCH(2) GARCH(1,1) EGARCH(1,1,2) IGARCH(1,1) TGARCH(1,1,2)
British Petroleum	AR(16) MA(1) MA(16)	GARCH(1,2) EGARCH(1,1,2) TGARCH(2,1,1)
BHP Billinton	AR(2) AR(8) MA(8)	GARCH(1,1) EGARCH(1,2,1) TGARCH(2,2,1)
Astra Zeneca	AR(4) MA(1) MA(3)	IGARCH(1,1) TGARCH(3,1,1)

Souce: Authors processing

Based on these models and on EWMA model, we forecasted the volatility for the period 18 May 2011- 31 May 2011 for all 4 stock options. After comparing with the real recorded values, we compute the forecast errors and then the values of the Theil indicators and Linex loss function. When comparing these values (Theil and LINEX), we could say for each time forecast horizon (1day, 5 days, 10 days) and each option (Rio Tinto, British Petroleum, BHP Billinton, Astra Zeneca) which is the model that generated the best and the worst forecast. The synthetic results are presented in table no. 3.

Table no. 3. *Best/ worst model in forecasting each options' volatility for the 3 time horizon considered*

Stock options	**1 day forecast**		**5 days forecast**		**10 days forecast**	
	Best model	**Worst model**	**Best model**	**Worst model**	**Best model**	**Worst model**
Rio Tinto	*ARCH*	*EWMA*	*IGARCH*	*EWMA*	*IGARCH*	*EWMA*
British Petroleum	*EWMA*	*GARCH*	*EWMA*	*GARCH*	*EGARCH*	*EWMA*
BHP Billinton	*TGARCH*	*EWMA*	*GARCH*	*EWMA*	*GARCH*	*EWMA*
Astra Zeneca	*IGARCH*	*EWMA*	*EWMA*	*IGARCH*	*EWMA*	*IGARCH*

Souce: Authors processing

Facing the situation in table no. 3, we can say that, by this, we concur to the already written idea in the literature that we cannot say that a best model exists, yet. But we can say that, for the considered period, options and forecast horizon, we considered the classical EWMA model to generate the biggest errors in most of the cases.

5. CONCLUSIONS

In this paper, we have investigated the forecasting performance of several GARCH class models and EWMA model. In the analysis that we made, we used those models to forecast out-of-sample of daily volatility for 4 stock options traded at Euronext London International Financial Futures and Options Exchange.

In order to pursue a fair comparison between the result, we used daily volatilities for the same period, ranging from the 1 January 2009 to 17 May 2011.

Our results suggest that the best forecast volatility models differ for every option and every forecast horizon; that is why we cannot pronounce whether a best model can be found, but, taking into consideration the used options and this specific period, we can conclude that the model that generates the biggest errors is EWMA.

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