A Study on Developing a VKOSPI Forecasting Model via GARCH Class Models for Intelligent Volatility Trading Systems

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Volatility plays a central role in both academic and practical applications, especially in pricing financial derivative products and trading volatility strategies. This study presents a novel mechanism based on generalized autoregressive conditional heteroskedasticity (GARCH) models that is able to enhance the performance of intelligent volatility trading systems by predicting Korean stock market volatility more accurately. In particular, we embedded the concept of the volatility asymmetry documented widely in the literature into our model.

The newly developed Korean stock market volatility index of KOSPI 200, VKOSPI, is used as a volatility proxy. It is the price of a linear portfolio of the KOSPI 200 index options and measures the effect of the expectations of dealers and option traders on stock market volatility for 30 calendar days. The KOSPI 200 index options market started in 1997 and has become the most actively traded market in the world. Its trading volume is more than 10 million contracts a day and records the highest of all the stock index option markets. Therefore, analyzing the VKOSPI has great importance in understanding volatility inherent in option prices and can afford some trading ideas for futures and option dealers. Use of the VKOSPI as volatility proxy avoids statistical estimation problems associated with other measures of volatility since the VKOSPI is model-free expected volatility of market participants calculated directly from the transacted option prices.

This study estimates the symmetric and asymmetric GARCH models for the KOSPI 200 index from January 2003 to December 2006 by the maximum likelihood procedure. Asymmetric GARCH models include GJR-GARCH model of Glosten, Jagannathan and Runke, exponential GARCH model of Nelson and power autoregressive conditional heteroskedasticity (ARCH) of Ding, Granger and Engle. Symmetric GARCH model indicates basic GARCH (1, 1). Tomorrow's forecasted value and change direction of stock market volatility are obtained by recursive GARCH specifications from January 2007 to December 2009 and are compared with the VKOSPI.

Empirical results indicate that negative unanticipated returns increase volatility more than positive return shocks of equal magnitude decrease volatility, indicating the existence of volatility asymmetry in the Korean stock market. The point value and change direction of tomorrow VKOSPI are estimated and forecasted by GARCH models. Volatility trading system is developed using the forecasted change direction of the VKOSPI, that is, if tomorrow VKOSPI is expected to rise, a long straddle or strangle position is established. A short straddle or strangle position is taken if VKOSPI is expected to fall tomorrow. Total profit is calculated as the cumulative sum of the VKOSPI percentage change. If forecasted direction is correct, the absolute value of the VKOSPI percentage changes is added to trading profit. It is subtracted from the trading profit if forecasted direction is not correct.

For the in-sample period, the power ARCH model best fits in a statistical metric, Mean Squared Prediction Error (MSPE), and the exponential GARCH model shows the highest Mean Correct Prediction (MCP). The power ARCH model best fits also for the out-of-sample period and provides the highest probability for the VKOSPI change direction tomorrow. Generally, the power ARCH model shows the best fit for the VKOSPI. All the GARCH models provide trading profits for volatility trading system and the exponential GARCH model shows the best performance, annual profit of 197.56%, during the in-sample period. The GARCH models present trading profits during the out-of-sample period except for the exponential GARCH model. During the out-of-sample period, the power ARCH model shows the largest annual trading profit of 38%.

The volatility clustering and asymmetry found in this research are the reflection of volatility non-linearity. This further suggests that combining the asymmetric GARCH models and artificial neural networks can significantly enhance the performance of the suggested volatility trading system, since artificial neural networks have been shown to effectively model nonlinear relationships.

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1. Introduction

The predictability of stock market volatility is important in pricing derivative products and trading volatility strategies. Volatility is a measure of stock price movement and has a time-varying and unstable nature. Stock market volatility has several salient features, including volatility clustering and asymmetry. A body of empirical research shows that Generalized Auto-gressive Conditional Heteroscedasticity (GARCH) models explain most of the volatility asymmetry documented in the U.S. stock market (Awartani and Corradi, 2005; Liu and Hung, 2010). Volatility asymmetry is also found in the Korean stock market (Ohk, 1997; Ku, 2000; Byun and

Jo, 2003).

The stylized facts help predict stock market volatility using particular time series models. The GARCH models proposed by Engle (1982) and Bollerslev (1986) seem to be the most successful. Symmetric and asymmetric GARCH models estimate conditional variance of stock returns via the maximum likelihood method. Moreover, a one-step ahead volatility forecast is readily available based on an iterative procedure. Hung (2009) suggests the fuzzy GARCH model and extracts the optimal parameters of the fuzzy membership functions and GARCH model using a genetic algorithm.

As volatility can not be directly observable, volatility proxies have been employed in empirically analyzing stock market volatility. Frequently used volatility proxy is a forward-looking volatility measure directly calculated from option prices. It is based on option market traded prices and shows expectations on future volatility among traders and option dealers. In 2003, the Chicago Board Options Exchange (CBOE) modified the CBOE Volatility Index (VIX) developed in 1993. This new index measures a weighted average of option prices across all strikes and soon became the most important benchmark for U.S. stock market volatility. It reflects expected volatility, one that continues to be widely used by financial theorists, risk managers and volatility traders alike. The Korea Exchange (KRX) also introduced a new CBOE VIX-like market volatility index called VKOSPI in 2009. VKOSPI provides a consensus of future volatility, not an estimate of current volatility, and as such plays an important role in analyzing Korean stock market volatility.

If we can forecast tomorrow's VKOSPI correctly, profits can be made by a well-established volatility trading strategy. Volatility trading involves traditional long or short volatility strategies. An example of the former is a long position in a straddle or strangle of call option and put option, since the position value usually increases with a rise in volatility. The short volatility strategy is widely used by institutional investors and a short position in a straddle or strangle is profitable with a decrease in volatility. Moreover, no change or small change in volatility can produce profit from wasted time premiums nested in option prices. Recently, some stock market exchanges have listed volatility contracts such as the VIX futures or options. This provides us a new profit opportunity through directly buying or selling a volatility index.

The purpose of this research is to compare the forecasting ability of the GARCH class models to predict both the point values and change directions of the VKOSPI, the Korean stock market volatility index. This study may be the first attempt to use the VKOSPI as the market volatility proxy in evaluating the predictive ability of the GARCH models. The forecasted volatility will be utilized to develop a volatility trading system for the Korean stock market.

In the next section the time series models used in the modelling and forecasting exercise are presented. In the third section the newly developed stock market volatility, VKOSPI, is discussed. The estimation and forecast of the GARCH models are performed and the volatility trading system is designed and tested in section four. The final section presents conclusions and limitations.

2. Time Series Models for Stock Market Volatility

Let $R_t = (\ln P_t - \ln P_{t-1}) \times 100$ denote the continuously compounded rate of returns from day t-1 to day t, where P_t is the price level of underlying index, KOSPI 200, at time t. The early generation of Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models, such as Autoregressive Conditional Heteroscedasticity (ARCH) model of Engle (1982) and GARCH model of Bollerslev (1986), can reproduce the volatility clustering phenomenon widely documented in the literature. The general GARCH(q, p) model with a basic mean can be formulated as follows :

$$R_t = \mu + \epsilon_t, \quad \epsilon_t \sim N(0,\, \sigma_t^2)$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2$$

where μ and σ_t^2 denote the conditional mean and variance of returns, ϵ_t is an unanticipated realized return at time t, that is, return shock at time t. Since σ_t^2 is the one-period ahead forecasted variance based on past market information, it is called the conditional variance. The conditional variance is a function of three terms :

- ◦ constant term : ω
- ◦ ARCH term : ϵ_{t-i}^2
- ◦ GARCH term : σ_{t-j}^2

The ARCH term means news information on the return shock from the previous period and has the order of p moving average terms. The GARCH term implies the last period's forecasted variance and has the order of q autoregressive terms. A commonly adopted parameterization for the GARCH (q, p) model is the (1, 1) specification under which the effect of a shock to volatility declines geometrically over time.

Although GARCH models reflect volatility clustering, they are symmetric. They cannot capture the volatility asymmetry that negative unanticipated return increases volatility more than positive return shocks of equal magnitude decrease volatility. To overcome this limitation, more flexible volatility specifications are introduced which allow positive and negative return shocks to have a different impact on volatility. Asymmetric GARCH models that meet the asymmetric volatility situation in response to positive and negative return shocks include the threshold GARCH model (GJR-GARCH) by Glosten et al.(1993), exponential GARCH model (EGARCH) of Nelson (1991), and power ARCH model(PARCH) of Ding et al.(1993). For comparison, the symmetric GARCH model is tested.

The GJR-GARCH model has the ability to forecast volatility using the moving average ARCH term and autoregressive GARCH term and adds a return shock term to GARCH model by :

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma\epsilon_{t-1}^2 I_{t-1} \;\; where \; I_{t-1} = 1 \text{ if } \epsilon_{t-1} < 0 \text{ and } 0 \; otherwise.$$

where the indicator variable I_{t-1} differentiates between positive and negative return shocks, so that asymmetric effects in the volatility are captured by γ. The parameter α measures the extent to which a squared return shock yesterday feeds through into future volatility, while the sum $\alpha+\beta$ measures the persistence of volatility. Thus, in the GJR-GARCH model, positive good news with a positive return shock has an impact of α, and negative news has an impact of $\alpha+\gamma$, with negative news having a greater effect on volatility if $\gamma > 0$.

The EGARCH model of Nelson (1991) provides an alternative asymmetric volatility model as follows :

$$\log(\sigma_t^2) = \omega + \alpha\left|\frac{\epsilon_{t-1}}{\sigma_{t-1}}\right| + \beta\log(\sigma_{t-1}^2) + \gamma\frac{\epsilon_{t-1}}{\sigma_{t-1}}$$

where the coefficient γ captures the asymmetric impact of return shocks on volatility. The EGARCH model forecasts the next day's volatility using today's stock price movement and today's volatility. Especially, this model considers the volatility asymmetry phenomenon widely documented in stock market volatility.

The PARCH model is set out in the following equations :

$$\sigma_t^\delta = \omega + \beta\sigma_{t-1}^\delta + \alpha(|\epsilon_{t-1}| - \gamma\epsilon_{t-1})^\delta \;\; where \;\; \delta > 0.$$

The power term δ captures both the conditional standard deviation ($\delta = 1$) and conditional variance ($\delta = 2$) as special cases. The negative asymmetry in the model is captured via the parameter $\gamma > 0$.

To complete the GARCH specification, an assumption about the conditional distribution of the error term is required. Commonly employed distributions are the normal distribution and Student's t-distribution. Kang and Yoon (2007) show that the t-distribution outperforms the normal distribution in the Korean stock market returns. They also find that the assumption of a Student's t-distribution is better for incorporating the tendency of asymmetric leptokurtosis in a return distribution. This study also estimates the GARCH models using a Student's t-distribution.

3. VKOSPI and data description

On 13 April 2009 KRX introduced the KRX Volatility Index, VKOSPI, and back-calculated the VKOSPI to 2003 using the CBOE VIX formula. It is the price of a linear portfolio of the KOSPI 200 index options and measures the market participants' expectations on the stock market volatility for 30 calendar days.

Use of the VKOSPI provides several advantages for analyzing stock market volatility. First, since the VKOSPI is directly calculated from market traded KOSPI 200 option prices, it reflects the reaction of traders and option dealers to the return dynamics of the stock market. Second, use of the VKOSPI avoids statistical estimation problems associated with other measures of volatility. Third, the VKOSPI is a good proxy for expected stock market volatility.

The KRX (2009) provides the computational process for the VKOSPI. The general formula for the VKOSPI at time t includes the nearest maturity volatility and the next nearest maturity volatility such as

$$\sigma_1^2 = \frac{2}{T_1}\sum_{1}^{n}\frac{\Delta K_i}{K_i^2}e^{rT_1}Q(K_i) - \frac{1}{T_1}[\frac{F_1}{K_0}-1]^2$$

$$\sigma_2^2 = \frac{2}{T_2}\sum_{1}^{n}\frac{\Delta K_i}{K_i^2}e^{rT_2}Q(K_i) - \frac{1}{T_2}[\frac{F_2}{K_0}-1]^2$$

σ_1^2 : $volatility\ on\ the\ nearist\ maturity\ options$

σ_2^2 : $volatility\ on\ the\ next\ nearist\ maturity\ options$

$T_1 : \frac{N_{T_1}}{N_{365}},\ T_2 : \frac{N_{T_2}}{N_{365}},$

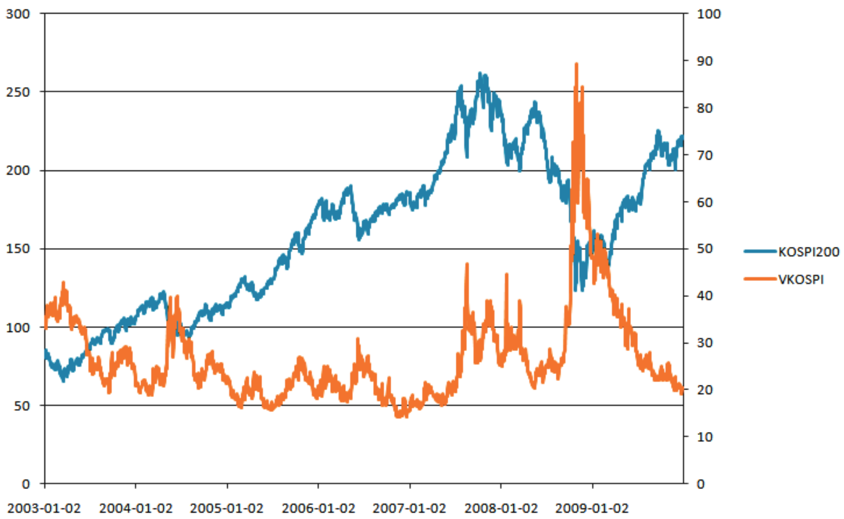
N_{T_1} : $remaining\ days$ for $the\ nearist\ maturity\ options$

N_{T_2} : $remaining\ days$ for $the\ next\ nearist\ maturity\ options$

where K_0 is the first strike price below the forward index level F_t, K_i is the strike price of the i-th out-of-the money option in the calculation, $\triangle K_i$ denotes the interval between strike prices, $Q(K_i)$ is the option's transacted prices with strike price K_i, and F_t denotes the time t forward index level. The final VKOSPI can be calculated as

$$VKOSPI = 100 \times \sqrt{\left\{T_1\sigma_1^2[\frac{N_{T_2}-N_{30}}{N_{T_2}-N_{T_1}}] + T_2\sigma_2^2[\frac{N_{30}-N_{T1}}{N_{T_2}-N_{T_1}}]\right\} \times \frac{N_{365}}{N_{30}}}$$

This study employs the daily KOSPI 200 stock price index from January 2003 to December 2009, a total of 1739 trading days, to estimate and forecast the GARCH models. The data



<Figure 1> VKOSPI and KOSPI 200 movement

from January 2003 to December 2006 is used in estimating the GARCH models and the data from January 2007 to December 2009 is used to test the estimated GARCH models' forecasting performance. The VKOSPI measures market volatility for 30 days. For comparison, 22-trading day windows are used as input data for the GARCH models. The daily VKOSPI index is used as a volatility proxy to compare the predictive ability of the GARCH models and develop a profitable volatility trading strategy. I obtain the daily close prices for the KOSPI 200 index and VKOSPI index from the KRX (www. krx.co.kr).

<Figure 1> shows the VKOSPI dynamics with the KOSPI 200 during the sample period. The VKOSPI generally moves between 20 and 40 and extremely rose to 89.30 during the 2008 global financial crisis. Generally, the VKOSPI has negative relation with the KOSPI 200 index.

<Table 1> presents the descriptive statistics of the VKOSPI and KOSPI 200 index returns for the sample period. The KOSPI 200 returns measured as a log difference have an average value of 0.0006, a maximum of 0.1154, and a minimum of -0.1090. The VKOSPI change rate, measured as log difference, has an average value of -0.0003, a maximum of 0.4157, and a minimum of -0.2159. The maximum value of the VKOSPI change rate is almost twice that of the minimum value and the skewness of the VKOSPI is positive and greater than that of the KOSPI 200. The VKOSPI and KOSPI 200 index both show larger kurtosis. Jarque-Bera statistics reject the normal distribution for the VKOSPI and KOSPI 200 returns and the Augmented Dickey- Fuller (ADF) statistics reject the existence of unit root.

<Table 1> Descriptive Statistics of the VKOSPI and KOSPI 200 returns

	KOSPI 200 return	VKOSPI change
mean	0.0582	-0.0321
median	0.1368	-0.3486
maximum	11.5397	41.5719
minimum	-10.9029	-21.5883
standard deviation	1.6402	5.0409
skewness	-0.3972	1.1344
kurtosis	7.9095	10.0945
Jarque-Bera	1791.18*	4017.62*
ADF	-41.2035*	-10.3505*

* : significant at 1% level.

4. Empirical Results

4.1 Estimation of GARCH Models

The GARCH models are estimated by the method of maximum likelihood using EViews 5.0. <Table 2> provides the estimation result for the GARCH models using the KOSPI 200 index from 2003 to 2006. The volatility asymmetry is found in the KOSPI 200 index. The γ s of GJR-GARCH, EGARCH and PARCH show that the conditional volatility is asymmetric in that GJR-GARCH $\gamma > 0$, EGARCH $\gamma < 0$ and PARCH $\gamma > 0$. EGARCH and PARCH models are better fitted than GARCH and GJR-GARCH models. The $\alpha + \beta = 0.972 < 1$ of the GARCH model proves that volatility is persistent and clustering.

4.2 Forecasting Results

To assess out-of-sample forecasting per-

<Table 2> Estimation for GARCH Models(2003～2006)

	μ	ω	α	β	γ	δ	Log L
GARCH	4.128 (41.41)**	2.322 (5.98)**	0.908 (6.68)**	0.064 (1.34)			-2758
GJR-GARCH	4.136 (39.88)**	2.431 (6.02)**	0.825 (5.22)**	0.057 (1.18)	0.126 (0.62)		-2758
EGARCH	3.865 (41.81)**	-0.423 (-3.07)**	1.404 (9.03)**	0.706 (11.75)**	-0.136 (-1.50)		-2764
PARCH	4.101 (37.60)**	3.779 (1.36)	0.967 (3.47)**	0.038 (0.76)	0.030 (0.51)	2.488 (2.62)**	-2762

** : significant at 1% level, Log L : Log Likelihood.

<Table 3> Forecasting performance comparisons of GARCH class models

	MSPE		MCP	
	in-sample	out-of-sample	in-sample	out-of-sample
GARCH	370.08	670.29	55.93	50.60
GJR-GARCH	369.56	669.60	55.52	50.87
EGARCH	376.61	704.74	57.17	50.47
PARCH	367.37	662.61	55.52	51.14

formance based on a statistical metric, Mean Squared Prediction Error(MSPE) is provided. It is the average squared deviation of the VKOSPI from the GARCH model's predicted volatility :

$$MSPE=\frac{1}{n}\sum_{t=1}^{n}(\sigma_t-\hat{\sigma}_t)^2$$

$where\ \sigma_t\ is\ the\ VKOSPI$ and $\hat{\sigma}_t\ is\ the\ predicted\ standard\ deviation\ at\ time\ t.$

Patton (2010) shows that MSPE is the most reliable metric, given that the forecast target is a proxy for volatility. The predictive accuracy of the VKOSPI change direction is an important factor for volatility trading purposes. For example, if the model predicts tomorrow's volatility decrease we can make a profit by taking a short straddle or strangle position. Likewise, a long straddle or strangle strategy will be profitable if the VKOSPI rises tomorrow. Chalamandaris and Tsekrekos (2009) suggest a Mean Correct Prediction (MCP) as an economic metric. It measures the percentage of the forecasted volatility which correctly predicts the sign of the VKOSPI change one day ahead and can be calculated as follows :

$$MCP=\frac{1}{n}\sum_{t=1}^{n}1_{sign(\sigma_t-\sigma_{t-1})=sign(\hat{\sigma}_t-\widehat{\sigma_{t-1}})}$$

$where\ 1\ means\ the\ change\ direction\ of\ the\ forecasted\ volatility$ and $the\ VKOSPI\ coincides.$

<Table 3> compares the forecasting performance of the GARCH models for the in-sample and out-of-sample periods.

For the in-sample period, the PARCH mo-

<Table 4> Trading profit comparisons for volatility trading system

	Total Profit		Annual profit	
	in-sample	out-of-sample	in-sample	out-of-sample
GARCH	685.25	99.45	171.31	33.15
GJR-GARCH	664.74	106.95	166.19	35.65
EGARCH	790.22	-30.84	197.56	-10.28
PARCH	655.40	114.01	163.85	38.00

del best fits in a statistical metric MSPE and the EGARCH model shows the highest MCP. The PARCH model best fits also for the out- of-sample period and provides the highest probability for the VKOSPI change direction tomorrow. Generally, the PARCH model of Ding et al. (1993) shows the best fit for the VKOSPI.

4.3 Volatility Trading System

To assess the economic significance of the forecasts formed by the GARCH models, the volatility trading system is proposed as follows:

If $\hat{\sigma}_t > \widehat{\sigma_{t-1}}$, then enter a long straddle position.
If $\hat{\sigma}_t < \widehat{\sigma_{t-1}}$, then enter a short straddle position.

<Table 4> provides the volatility trading system performance for the GARCH models. Total profit is calculated as the cumulative sum of the VKOSPI percentage change. If the forecasted direction is correct, the absolute value of the VKOSPI percentage changes is added to the trading profit. It is subtracted from the trading profit if the forecasted direction is not correct. All the GARCH models provide trading profits for the volatility strategy and the EGARCH model shows the best performance, an annual profit of 197.56%, during the in-sample period. The GARCH models present trading profits during the out-of-sample period except for the EGARCH model. During the out-of-sample period the PARCH model shows the largest annual trading profit of 38%.

5. Conclusions and Limitations

If stock market volatility is forecasted correctly, we can have a profit opportunity with financial derivatives products. We can buy an undervalued option in comparison with volatility to profits and sell an overvalued option to profits. If volatility is forecasted to increase, we can make a profit by buying both call and put options. If future volatility is expected to fall, selling both call and put options will give us profits. This is a typical volatility trading strategy. Stock market volatility has several striking features, including volatility clustering and asymmetry. These stylized facts help forecast future stock market volatility more accurately than future stock returns. The asymmetric GARCH models for the KOSPI 200 index properly reflect the volatility asymmetry found in empirical research. This study presents several salient points. First, the asymmetric GARCH models such as the GJR-GARCH, EGARCH and PARCH show that volatility is asymmetrically related with stock returns. Specifically, GJR-GARCH $\gamma > 0$, EGARCH $\gamma < 0$ and PARCH $\gamma > 0$. Second, the EGARCH model shows the worst forecasting performance for the in-sample period and the PARCH model provides best forecasting performance for the out-of-sample period. Finally, the trading profits for volatility strategies are obtained from the GARCH models for the in-sample and out-of-sample period except for the EGARCH model.

The Korean stock market volatility also shows volatility persistence and clustering effects, that is, $\alpha + \beta < 1$ in the symmetric GARCH model from <Table 2>. This means simply that large price changes tend to beget other large price changes and small price changes beget other small price changes. The profit performance of our volatility trading system can be enhanced significantly by combining the asymmetric GARCH models found in this study and fuzzy systems.

This study has some limitations. Statistical time series models of GARCH can cause some problems in describing stock market because it is very noisy and non-linear. A new class of artificial intelligence models will be needed to overcome the problems for future research. Time premiums inherent in option prices are not considered. They may have complicated effects on the profit-loss curve of the volatility strategies. Transaction costs are ignored, which would overestimate the trading profit from the volatility strategies.

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Abstract

지능형 변동성트레이딩시스템개발을 위한 GARCH 모형을 통한 VKOSPI 예측모형 개발에 관한 연구

김선웅*

학계와 금융파생상품 가격결정이나 변동성매매와 같은 실무영역 모두에서 주식시장의 변동성은 중요한 역할을 한다. 본 연구는 GARCH 모형에 기초하여 한국주식시장의 변동성을 정확히 예측함으로써 변동성매매시스템의 성과를 높일 수 있는 새로운 방법을 제시하였다. 특히, 여러 연구 자료에서 밝혀지고 있는 변동성 비대칭성개념을 도입하였다.

최근 새로 개발된 한국주식시장 변동성 지수인 VKOSPI를 변동성 대용값으로 사용한다. VKOSPI는 KOSPI 200 지수옵션의 가격을 이용하여 계산된 값으로서 옵션딜러들의 변동성 예측치를 반영하고 있다. KOSPI 200 옵션시장은 1997년 시작되었으며, 발전을 거듭하여 현재 하루 거래량이 1,000만 계약을 넘어서면서 세계 최고의 지수옵션시장으로 발전하였다. 이러한 옵션시장에 반영된 변동성을 분석하는 것은 투자자들에게 좋은 투자정보를 제공하게 될 것이다. 특히, 변동성 대용값으로 VKOSPI를 사용하면 다른 변동성 대용치를 사용할 때 발생하는 통계적 추정의 문제를 피해 갈 수 있다.

본 연구는 2003년부터 2006년의 KOSPI 200 지수 일별자료를 대상으로 최우도추정방법(MLE)을 이용하여 GARCH 모형을 추정한다. 비대칭 GARCH 모형으로는 Glosten, Jagannathan, Runke의 GJR-GARCH 모형, Nelson의 EGARCH 모형, 그리고 Ding, Granger, Engle의 PARCH모형을 포함하며 대칭 GARCH 모형은 (1, 1) GARCH 모형을 이용한다. 2007년부터 2009년까지의 KOSPI 200 지수 일별자료를 대상으로 반복적 계산과정을 통해 내일의 변동성 예측값과 오르고 내리는 변화방향을 예측하였다.

분석 결과 시장변동성과 예기치 않은 주가변동 사이에는 음의 상관관계가 존재하며, 음의 주가변동은 동일한 크기의 양의 주가변동보다 훨씬 더 큰 변동성의 증가를 가져옴을 알 수 있다. 즉, 한국주식시장에도 변동성 비대칭성이 존재함을 보여주었다. GARCH 모형을 이용하여 내일의 VKOSPI의 등락방향을 예측하고 이를 이용하여 변동성 매매시스템을 개발하였다. 내일의 변동성이 상승할 것으로 예측되면 스트래들매수전략을 이용하고 반대로 변동성이 하락할 것으로 예측되면 스트래들

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매도전략을 이용한다. 변동성의 변화방향성을 맞춘 경우에는 VKOSPI 변동분을 더하고 틀린 경우에는 변동분을 뺀 누적합을 이용하여 변동성매매전략의 총수익을 계산한다.

모형추정용 자료구간의 경우 통계적 기준인 MSPE 기준으로는 PARCH 모형의 적합도가 가장 높고, 예측방향의 적중도를 재는 MCP 기준으로는 EGARCH 모형이 가장 높은 값을 보여주었다. 테스트용 자료구간의 경우에는 PARCH 모형이 모형적합도와 내일의 변동성 등락방향 예측에서 가장 좋은 결과를 보여주었다. 모형추정용 자료구간의 경우 GARCH 모형 전체에서 매매이익을 기록하고 있고 테스트용 자료구간의 경우에는 EGARCH 모형을 제외한 GARCH 모형들이 매매이익을 보여주었다.

본 연구에서 나타난 변동성의 군집과 비대칭성 현상으로부터 변동성에 비선형성이 존재함을 알 수 있었으며, 비선형성에서 좋은 결과를 보이고 있는 인공지능시스템과 비대칭 GARCH 모형을 결합한다면 제안된 변동성매매시스템의 성과를 많이 개선할 수 있을 것으로 판단된다.

Keywords : VKOSPI, 변동성비대칭성, GARCH, 변동성트레이딩시스템

저 자 소 개

김선웅

현재 국민대학교 비즈니스IT전문대학원 초빙교수로 재직 중이다. 서울대학교 경영학과에서 경영학사를 취득하고, KAIST 경영과학과에서 증권투자론을 전공하여 공학석사와 박사를 취득하였다. 주요 관심분야는 투자공학, 트레이딩시스템, 헤지펀드와 자산운용이다.