Volatility Spillover Effect between U.S. and Japanese Stock Markets

Sung-Yong Park, Sang Hoon Kang, and Seong-Min Yoon

***Abstract*—**According to the rapidly changing global economy market movement, financial market participants show higher interest about the volatility and are curious about the mutual relationship between volatility and rate of change of the stock market, which is the center of financial market.

This research uses the daily data, NIKKEI 224 index, and Dow-Jones Index for the rate of change of stock index income rate. The conditional rate of change is estimated with the GARCH (1,1) Model, and the mutual relationship between volatility and change rate is analyzed with the BEKK model.

As a result of the vitality inspection result between both markets, shock transition effect was identified in the symmetric GARCH Model. In the asymmetric GARCH Model, shock transition effect was identified form Dow-Jones market to NIKKEI 225 Market.

Thus, asymmetric volatility transition means the bad news of Dow-Jones represents greater volatility in the NIKKEI 225 Market than the good news of Dow-Jones. Moreover, while Dow-Jones market information is transferred to NIKKEI 225 market, Dow-Jones market's price gives influence on NIKKEI 225 Market.

***Keywords*—**Asymmetric volatility transmission; Causality; Cointegration; GARCH-BEKK model; Volatility spillover effect, Dow-Jones, NIKKEI 225.

I. Introduction

NO one can be free in the rapidly changing global economic market. America- the center of global economy- showed a plunge in the global stock market after 9.11 Incident in 2011, Iraq War in 2003, and subprime mortgage mess occurred.

The volatility of the stock market [1-6] gives influence on the financial market and also brings bad results to the global economy. For example, fund brokerage reduces where production and efficiency of companies become lower. Moreover, flexibility drops for investors where it becomes harder to find information of the investment. Furthermore, there is bad influence on open market rate, which eventually becomes a cause of economic delay. Thus, it is important to provide accurate volatility prediction [7] and macroeconomics [8,9]. Macroeconomic variable's change has a close relationship with the stock price [10]. Research on volatility transition phenomenon was started based on the stock market with the BAR method. Here, it was identified that 9 countries of the world, starting from America's stock market, was receiving volatility shock transition [11]. It was verified on the bad news rather than the good news that volatility transition effect of America, England, and Japan, which multivariate EGARCH, was clearer [12]. Also, theoretical research related to the asymmetric volatility [13,14] was identified to have time-variable characteristic that changes according to the flow of time and grouping phenomenon. When considering the rapidly changing phenomenon, it was identified that long-term memory characteristic is disappearing. This means that excessive prediction is made on the volatility durability in the analysis of actual proof result [15]. This research considered the information transition effect and volatility transition effect between the stock price of NIKKEI 225 and Dow-Jones Market. This research also has a purpose of quantifying the influence between the two markets.

Also, bivariate GARCH BEKK model is used to analyze the mutual relationship between shock, volatility, and change rate of Dow-Jones market and NIKKEI 225 Market through BEKK Model.

The main contents of this research are composed as the following. Chapter 2 proposes econometric methodology. – Cointegration test, symmetric/asymmetric bivariate GARCH model in particular. This research also investigates whether good news brings greater volatility on other market than good news. Chapter 5 is the conclusion.

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II. Methodology

A. Bivariate GARCH model

Please submit your manuscript electronically for review as e-mail attachments. When you submit your initial full paper version, prepare it in two-column format, including figures and tables. Policy makers or financial market participants are interested in whether news of a market has influence in the volatility of another market. In this research, we use the bivariate framework of BEKK parameterization [16] to analyze the volatility relationship between two stock markets. In this model, variance-covariance matrix relies on squares matrix while cross products of innovation relies on ε_t. This can be calculated due to the average equation as shown in equation (1):

$$R_t = a + \varepsilon_t,\ \ \varepsilon_t \mid \varphi_{t-1} \sim N(0, h_t) \tag{1}$$

R_t identifies each market income rate in t (time) while ε defines each market's innovation during t-time.

φ_{t-1} is the information of a market that is available during t-1 (time).

To resolve the plus sign problem of GARCH BEKK [17] Model, it is the model that gives secondary equation form. GARCH-BEKK model's dispersive equation is shown in equation (2).

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B \tag{2}$$

Here, H_t is the variance-covariance matrix of t time, ε_{t-1} is $t-1$ residual vector, A is square matrix, , B is the square matrix that measures the relationship between conditional dispersion of before with the current conditional dispersion, and C is the lower part triangular matrix of the variables, which can be re-organized as equation (3).

$$H_t = \begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{bmatrix} = \begin{bmatrix} c_{11} & \\ c_{21} & c_{22} \end{bmatrix}' \begin{bmatrix} c_{11} & \\ c_{21} & c_{22} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}\varepsilon_{1,t-1} & \varepsilon_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}' \begin{bmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \tag{3}$$

$h_{11,t}$ represents the volatility of market returns, $h_{12,t}$ represents the covariance of Dow-Jones Market and NIKKEI 225 market returns, respectively; lastly, $h_{22,t}$ represents the volatility NIKKEI 225 market returns. $a_{11}(a_{12})$ coefficients located diagonally defines the relationship with squared errors of $h_{11,t}\,(h_{22,t})$.

On the other hand, $h_{11,t}\,(h_{22,t})$ was identified that the current conditional volatility of $h_{11,t}\,(h_{22,t})$ gives influence on the existing conditional volatility.

Also, coefficients a_{12} and b_{12} , which are located off-diagonally, represent the effect of volatility that Dow-Jones market gives on NIKKEI 225 market. On the other hand, a_{21} and b_{21} shows effect of volatility that NIKKEI 225 market gives on Dow-Jones market.

Also, volatility has the tendency of responding to bad news rather than good news [18, 19].

Asymmetric dispersive equation is shown on equation (4) and (5).

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B + D'\theta_{t-1}\theta'_{t-1}D \tag{4}$$

$$\begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{bmatrix} = \begin{bmatrix} c_{11} & \\ c_{21} & c_{22} \end{bmatrix}' \begin{bmatrix} c_{11} & \\ c_{21} & c_{22} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}\varepsilon_{1,t-1} & \varepsilon_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}' \begin{bmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} + \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix}' \begin{bmatrix} \theta_{1,t-1}^2 & \theta_{1,t-1}\theta_{2,t-1} \\ \theta_{2,t-1}\eta_{1,t-1} & \theta_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix} \tag{5}$$

$$\theta_{t-1} = \begin{bmatrix} \max\left(0, -\varepsilon_{1,t-1}\right) \\ \max\left(0, -\varepsilon_{2,t-1}\right) \end{bmatrix}$$

D is the squared matrix, and θ_{t-1} is set to calculate the covariance and irregular volatility. If $d_{12}\,(d_{21})$ coefficient has significance in value of quantity, Dow Jones Market (or NIKKEI 225)'s bad news volatility causes high volatility in NIKKEI 225 (or Dow Jones).

Bivariate GARCH Model's variables are measured due to the Maximum likelihood estimation method through Berndt, Hall, Hall, and Hausman (BHHH) algorithm.

Conditional log linear model $L(\lambda)$ is identified in equation (6).

$$L(\lambda) = -T\log 2\pi - \frac{1}{2}\sum_{t=1}^{T}\left(\log\left|H_t(\lambda)\right| + \varepsilon_t' H_t^{-1}\varepsilon_t(\lambda)\right) \tag{6}$$

T defines the observed number and λ is the unknown vector.

III. Data And Descriptive Statistics

This research analyzes the movement of information between America and Japan's stock market. The data used for the analysis data are composed of financial information, media service companies, Dow Jones industry index, and transportation industry index, which hold global reputation. Moreover, the price of Dow Jones index and 225 types with high flexibility in Tokyo Stock Exchange are selected as target where they are traded with Osaka Stock Exchange, Chicago Mercantile Exchange (CME), and Singapore Stock Exchange (SGX). Lastly, NIKKEI 225 future index price that is considered as a main future index internationally is also used. The data of this research is provided by Louis Bank composed of Daily Closing Prices from January 4th, 1990 to October 31st, 2014 (Total of 5,916 times measured). The reason for the moving stock prices is mostly related to macroeconomic variable and financial policy.

For example (1) America's economy in the 1990s were structured as new economic system based on finance and information industry and based in long term prosperity for more than 10 years. On the other hand, Japan was not able to get out of 10 years of real estate bubble collapse phenomenon.

(2) Venture business development in 2000s increased the stock price along with financial policy that was needed for Japan's economy, but the vicious economic circle of economy did not stop while America's market's started to go on a rapid decrease along with big losses due to IT bubble.

(3) September 11th terror incident in 2001 and the Iraq War

that started in March of 2003 led to the steep decline of the global stock market.

(4) America's subprime mortgage incident, which made the whole world's economy into depression in the end of 2007, brought America, Japan, and other global markets to great depth from 2007-2008.

(5) Along with the rapidly changing financial crisis such as 2013 America's Exit plan and Abenomics economic policy, Yen and Japan's stock market was in long-term depression.

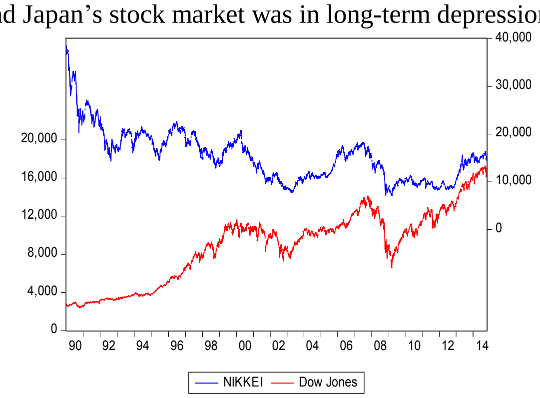

Fig. 1 Daily Dow Jones and NIKKEI 225 Price Movements

Figure 1 is the daily Dow Jones index and NIKKEI 225 inde x price movement from January 4th, 1990 to October 31st, 201 4, identified on a graph. The numbers on the left identify Dow Jones Index and the numbers on the right identify NIKKEI 225 index.

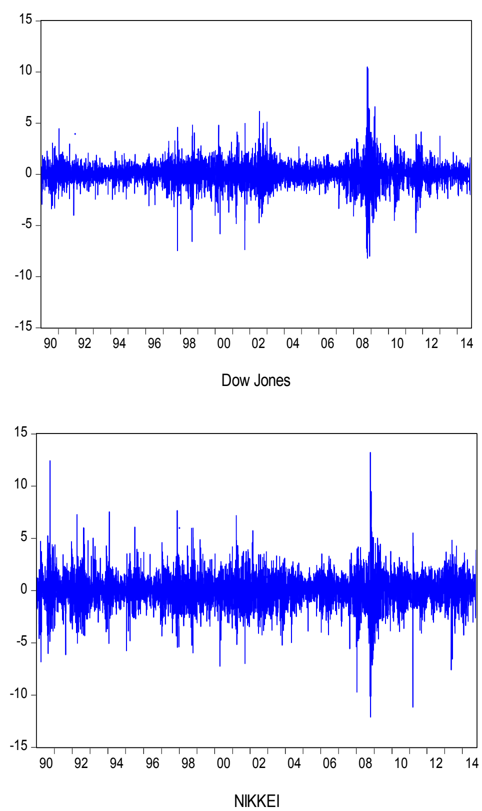

Fig. 2 Daily Stock Price Income Rate

The return series of the two samples is $t = 1, 2, \cdots, T$, which is calculated by $R_{i,t} = \ln\left(p_{i,t} / p_{i,t-1}\right) \times 100$, Here, $R_{i,t}$ means the compounded returns of i during t period, and $P_{i,t}$ identifies closing price of indices of i during t period.

The volatility of the two sample incomes can be seen on Figure 2 and shows volatility clustering. Volatility clustering means the phenomenon that raises the possibility that current volatility will influence the future volatility.

TABLE I
DESCRIPTIVE STATISTICS OF SAMPLE RETURNS

	Dow Jones	NIKKEI 225
Mean	0.030894	-0.014504
Std.dev	1.118385	1.569829
skewness	-0.145120	-0.154822
kurtosis	-18450.68	-18205.50
Jarque-Bera	15707.16***	6988.85***
$LB^2(32)$	7831.966***	4149.293***

Notes: The J-B corresponds to the test statistic for the null hypothesis of normality in sample returns distribution. The Ljung-Box statistic, $LB^2(32)$, checks for the serial correlation of the squared returns up to the 32nd order. *** indicates the rejection of the null hypothesis at the 1% significance level

Table 1 shows the descriptive statistics of income volatility of the two samples. The sample average of income is very small and it was identified that the standard deviation of the income was high. Income distribution was not regularly distributed as seen on skewness, kurtosis, Jarque-Bera test.

Moreover, the null hypothesis in accordance with Ljung-Box statistics is dismissed as 1% significance.

$LB^2(20)$ is Ljung-Box statistics about the interrelationship of the series.

These results prefer the model that includes the characteristics of ARCH/GARCH.

TABLE II
RESULTS OF UNIT ROOT TEST FOR LOG PRICE AND RETURNS

	Dow Jones		NIKKEI 225	
	Log Price	returns	Log Price	returns
ADF	-1.304	-58.36***	-2.988**	-57.13***
[prob]	[0.629]	[0.000]	[0.036]	[0.000]
PP	-1.296	-80.51***	-0.295	-78.32***
[prob]	[0.633]	[0.000]	[0.396]	[0.000]

Note: [20] 1% critical value is –3.435 for the ADF and PP tests

Table 2 shows the result of Augmented Dickey-Fuller (ADF), log price series, Phillips-Perron (PP) unit root tests of return series.

ADF and PP verification's null hypothesis show that unit root exists in time series.

As shown on Table 2, the values measured in ADF and PP verification show that log price series has 1% significant unit root in Dow Jones. On the other hand, the null hypothesis of unit root is rejected in NIKKEI 225. This is because the log price series of Dow Jones changes and NIKKEI 225's sample is fixed. However, in return series, both statistics reject null hypothesis of a unit root in 1% significance, and this means that the return series is fixed in all samples.

IV. Empirical Results

TABLE III
RESULTS OF JOHANSEN COINTEGRATION TEST

null hypothesis	Trace Statistic	0.05 critical value	Max-eigen Statistic	0.05 critical value
$r=0$	14.57	15.49	11.42	14.26
$r \le 1$	3.148	3.841	3.148	3.841

Notes: ** denotes rejection of the hypothesis at the 5% significance level. The reported critical values are the [21] critical values.

Table 3 shows the results of Johansen Cointegration test of return series of Dow-Jones Index and NIKKEI 225 Index. Trace statistics is 14.57, but this falls short by 5% of the threshold value of 15.49 and also marks the null hypothesis that does not have 5% significance level for covariance. Similarly, Max-eigen Statistic is 11.42, and this marks the null hypothesis that does not have 5% significance level for covariance. However, in $H_0 : r \le 1$, Trace Statistic and Max-eigen Statistic are simultaneously 3.148, which falls 5% short from the critical value of 3.841. Thus, % significance level of the null hypothesis of one cointegration must be accepted. Eventually, there is no covariant relationship between Dow Jones Index and NIKKEI 225 Index, which also means that there is no long-run cointeraction between the two affiliations.

TABLE IV
ESTIMATION RESULTS OF THE GARCH-BEKK MODEL

Variable	Symmetric Coefficient	Std.error	Asymmetric Coefficient	Coefficient
Panel A: Symmetric and asymmetric GARCH (1, 1)-BEKK estimations				
c_{11}	0.115***	(0.006)	0.125***	(0.005)
c_{21}	-0.014***	(0.027)	-0.000***	(0.025)
c_{22}	0.253***	(0.012)	0.227***	(0.014)
a_{11}	0.249***	(0.007)	-0.076***	(0.018)
a_{12}	-0.072***	(0.009)	0.194***	(0.013)
a_{21}	-0.004***	(0.006)	0.008***	(0.008)
a_{22}	0.292***	(0.008)	0.198***	(0.012)
b_{11}	0.962***	(0.002)	0.960***	(0.002)
b_{12}	0.027***	(0.003)	0.295***	(0.006)
b_{21}	-0.000***	(0.002)	-0.000***	(0.003)
b_{22}	0.941***	(0.003)	0.930***	(0.004)
d_{11}			-0.341***	(0.010)
d_{12}			0.084***	(0.023)
d_{21}			0.018***	(0.010)
d_{22}			-0.309***	(0.014)
Panel B: Diagnostic tests				
$LB_1^2(20)$	28.85(0.090)		14.30(0.814)	
$LB_2^2(20)$	19.21(0.507)		14.32(0.813)	
$ARCH_1(20)$	23.85(0.247)		21.45(0.370)	
$ARCH_2(20)$	20.63(0.419)		20.55(0.423)	
log-likelihood	-18450.68		-18205.50	

Notes: P-values are in brackets and standard errors are in parenthesis. The $ARCH_i(20)$ test statistic checks the remaining ARCH effects in standardized residuals. The $LB_i^2(20)$ test statistic checks for the serial correlation of squared standardized residuals. ** and *** indicate significance at the 5% and 1% levels, respectively.

Bivariate GARCH model's important coefficients are $a_{i,i}$ and $b_{i,i}$ values of A and B, where $i=1$ represents Dow-Jones and $i=2$ represents NIKKEI 225

Matrix A and Matrix B are the values that measured the past volatility effect and existing shock effect.

In the table, the variables (b_{11} and b_{22}) that are located diagonally from Matrix B are statistically significant, and this gives influence in conditional volatility of both markets while representing that strong GARCH effect exists.

Lao, the variables (a_{11} and a_{22}) that are located diagonally are significant while representing the existing of ARCH effect in both markets.

Matrix A and Matrix's off-diagonal values show the effect between markets like the volatility transition effect and shock effect of Dow-Jones market and NIKKEI 225 market.
Symmetric GARCH Model shows the shock transition effect between both markets, which is because coefficients a_{12} and a_{21} have negative and significant values.

Also, in the symmetric/asymmetric GARCH Model, The volatility market in one direction of Dow-Jones market and NIKKEI 225 market can be checked. For example, the volatility of Dow-Jones market in the past increases the current volatility of NIKKEI 225. This is because coefficient b_{12} has both values. This also means that Dow-Jones market gives greater influence on volatility of NIKKEI 225 Market.

Also, from Matrix D, coefficients d_{11} and d_{22}, which are related to both market's income, are significant. Moreover, asymmetric response of bad news can be checked. This identifies that bad news has greater influence in the volatility of both markets compared to the good news. Because coefficient d_{12} has 1% significance and both values, asymmetric response exists as NIKKEI 225 Market in Dow-Jones Market. This represents that rather than the good news, the bad news of Dow-Jones market has brings great volatility in NIKKEI 225.

V. Conclusions

In this paper, Bivariate GARCH-BEKK model was used to investigate the mutual relationship between the change rate and volatility of two stock markets. Especially, the symmetric/asymmetric volatility transition between Dow-Jones Market and NIKKEI 225 Market was studied. In the symmetric/asymmetric GARCH model, the shock transition effect between both markets was identified, and the empirical also shows the both directional volatility transition from Dow-Jones market to NIKKEI 225 market. The more important thing is that Dow-Jones market's bad news increases the volatility of NIKKEI 225 market when compared to good news. Thus, these results represent that Dow-Jones market gives important influence in the volatility of NIKEEI 225 market.

Also, when applying the results from above to the stock market, volatility clustering is identified in the volatility. This increases the possibility that volatility will be growing for a while. It can be used in making Straddle or Strangle Strategies in the stock market.

When volatility expansion is expected, price reduction of Dow-Jones when buying stocks bring out active fund of NIKKEI 225 market through volatility transition effect of Dow-Jones Market; on the other hand, when selling stocks in Strangle, bad news of Dow-Jones increases the volatility of NIKKEI 225 market. However, because the price information is reflected on the volatility, it will not be easy to have command of the strategy above.

This research has hopes that it will help in future researches for considering about the resolution of how financial market participants look at these kinds of services.

Furthermore, this research that did not consider the rapidly changing phenomenon will be supplemented through the research of Yoon, S. M. and S. H. Kang (2012).

References

[1] Sadorsky, P., 1999. Oil price shocks and stock market activity. Energy Economics 21, 449-469.
http://dx.doi.org/10.1016/S0140-9883(99)00020-1

[2] Sadorsky, P., 2001. Risk factors in stock returns of Canadian oil and gas companies. Energy Economics 23, 17-28.
http://dx.doi.org/10.1016/S0140-9883(00)00072-4

[3] Sadorsky, P., 2012. Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies. Energy Economics 34, 248-255.
http://dx.doi.org/10.1016/j.eneco.2011.03.006

[4] Malik, F., Hammoudeh, S., 2007. Shock and volatility transmission in the oil, US and Gulf equity markets. International Review of Economics and Finance 16, 357-368.
http://dx.doi.org/10.1016/j.iref.2005.05.005

[5] Aloui, C., Jammazi, R., 2009. The effects of crude oil shocks on stock market shifts behaviour: a regime switching approach. Energy Economics 31, 789-799.
http://dx.doi.org/10.1016/j.eneco.2009.03.009

[6] Chiou, J.-S., Lee, Y.-H., 2009. Jump dynamics and volatility: oil and the stock markets. Energy 34, 788-796.
http://dx.doi.org/10.1016/j.energy.2009.02.011

[7] Andersen and Bollerslev (1998) show that GARCH models provide accurate volatility forecasts provided that volatility persistence is accurately estimated.

[8] Lee, B.R., Lee, K., Ratti, R.A., 2001. Monetary policy, oil price shocks, and the Japanese economy. Japan and the World Economy 13, 321-349. http://dx.doi.org/10.1016/S0922-1425(01)00065-2

[9] Rafiq, S., Salim. R., Bloch, H., 2009. Impact of crude oil volatility on economic activities: an empirical investigation in the Thai economy. Resources Policy 34, 212-132.
http://dx.doi.org/10.1016/j.resourpol.2008.09.001

[10] Fama, E., "Stock returns, real activity, inflation, and money", American Economic Review 71(1981), 545-565

[11] Eun, C. S. and S. Shim(1989). "International Transmission of Stock", Market Movements." Journal of Financial and Quantitative. Analysis. Vol. 24. No. 2, pp. 241-256. http://dx.doi.org/10.2307/2330774

[12] Koutmos, G.,& Booth, G.G (1995). Symmetric Volatility Transmission in International Stock Markets. Journal of Money and Finance, 14,747-762. http://dx.doi.org/10.1016/0261-5606(95)00031-3

[13] Fama, E. F. (1965), "The Behavior of Stock Market Prices," Journal of Business, 38, 34-105. http://dx.doi.org/10.1086/294743

[14] Engle, R. F. (1982), "Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of United Kingdom Inflation," Econometrica, 50, 987-1007. http://dx.doi.org/10.2307/1912773

[15] Yoon, S. M. and S. H. Kang (2012). Sudden Changes and Long Memory: "Forecasting the Volatility of Asian Stock Markets". POSRI Business Review 12(3),183-213.

[16] Engle, R.F., Kroner, K.F., 1995. Multivariate simultaneous generalized ARCH. Econometric Theory 11, 122-150. http://dx.doi.org/10.1017/S0266466600009063

[17] Engle, Robert F. and Victor K.. Ng, 1993, "Measuring and Testing the Impact of News on Volatility," Journal of Financial, 48(5), 1749-1778. http://dx.doi.org/10.1111/j.1540-6261.1993.tb05127.x

[18] Engle, R.F., Ng, V.K., 1993. Measuring and testing the impact of news on volatility. Journal of Finance 48, 1749-1778. http://dx.doi.org/10.1111/j.1540-6261.1993.tb05127.x

[19] Kroner, K.F., Ng, V.K., 1998. Modeling asymmetric comovements of asset returns. Review of Financial Studies 11, 817-844. http://dx.doi.org/10.1093/rfs/11.4.817

[20] MacKinnon, J.G., 1991. Critical values for cointegration tests. In: Engle, R.F., Granger, C.W.J. (Eds.), Long-Run Economic Relationships: Readings in Cointegration, Oxford University Press, New York, 266-276.

[21] Osterwald-Lenum, M., 1992. A note with quantiles of the asymptotic distribution of the maximum likelihood cointegration rank test statistics. Oxford Bulletin of Economics and Statistics 54, 461-471. http://dx.doi.org/10.1111/j.1468-0084.1992.tb00013.x