Socrates Journal of Interdisciplinary Social Studies ISSN: 2757-5519

ESTIMATING THE VOLATILITY OF STOCK MARKETS IN CASE OF FINANCIAL CRISIS

Dr. Gültekin GÜRÇAY

ABSTRACT

In this paper, effects and responses of stock were analyzed. This analysis was done periodically. Thedimensions of the financial crisis impact on the stock market was investigated by GARCH model. In this context, S&P 500 stock market are modeled with DAX, NIKKEI and BIST100. In this way, the effects of the changing in S&P 500 stock market were examined on European and Asian stock markets. Conditional variance coefficient will be calculated through garch model. The scope of the crisis period, the conditional covariance coefficient will be analyzed comparatively.

Keywords: Conditional variance coefficient, financial crisis,Garchmodel,stock market.

I. INTRODUCTION

BETWEEN 2005 and 2014, the S&P 500, DAX and NIKKEI 100 BIST by taking the logarithm of the closing stock index returns are calculated. These data were used in the model. GARCH (1,1) model was estimated in the EViewsprogram.Engle, R. (2007) argued that volatility is a fundamental factor in the global financial market. It is related with the risk that can be taken in order to have rewards. Risk and rewards are correlated each other but it is necessary to have a certain optimal behaviour in order to take risk, which can perform positive returns. So we choose a portfolio optimization position witch minimize the risk and maximize the rewards. Risk is determined by the variance of a portfolio in Markowitz (1952) theory for optimization. The same relationship between returns and variance can be sown in CAMP financial model which is introduced by Sharpe (1954). Moreover, risk can be determined very well by Black and Scholes (1972) model which is used in order to estimate the value of options in financial derivatives. The square route of variance is called volatility. Volatility is the standard deviation of the stock returns in a period of time. It is changing over time as it is presented by the analysts. We have different values of volatility in different time periods. Two basic types of volatility is the historical volatility and news volatility. The last is based on the element of information because every investor or risk manager would like to know if a small company will be developed in the future or not. Big companies give small volatility in contrast with small companies which give high volatility. So, if somebody knows that in a short period of time a company that is already small will be developed then he can arrange his investments in order to have arbitrage opportunities. Historical volatility, which is widely used, is estimated by historical data and it equals to the standard deviation of stock returns in a period of time. But if we get a short number of observations we will get noisy results and if we take a long series we will get smooth results which are not responding to the recent information. Historical volatility does not respond to that situation. ARCH models with their extensions come to fill this gap. ARCH (Autoregressive Conditional Heteroscedasticity) is introduced by Robert Engle in 1982 who won the Nobel price about that in 2003. ARCH volatility gives weights between the recent data and the data which are provided by information that happen a long time ago. The special feature of ARCH model is that it can calculate these weights based on historical data. There are lot extensions of ARCH models which describe non-linearity, asymmetry and long memory properties of volatilityas dependent variables, DAX and NIKKEI BIST 100 were taken. As independent variables, lag(1) of S&P 500 and lag(1) of each stock market were taken. In addition to model, unit root test and correlogram analysis were performed for each variables. In this way, the validity of the model will be tested. According to the Garch(1,1) model we will measure the effect size of financial crises (2008-2009) on stock markets.The graph (Garch 1,1) shows the evolution of the stock markets..

II. METHOD

First of all, logarithm is taken of all the variables. The yield was calculated based on the data log was taken. Unit root tests were performed for all variables. In case of not being root volume, the model will be established for each model, longer termscorrelogram analysis will be carried out. In case of not being autocorrelation in all models, established models will be reviewed.The key feature of volatility clustering is that shows the periods in which the market can be characterized by low or high volatility.If the returns are shown to have large dispersion then this period of time can be characterized by high volatility in the market and if the returns are appeared to have low dispersion, this period of time can be characterized by low volatility in the market.

III. RESULTS

ADF and PP test were performed all variables. For each tests, the prob value is less than 0,05. Due to the ADF and PP unit root tests, DAX, S&P500, NIKKEI and BIST100 has not unit root. In this instance, returns of variables will be used in garch model.

TABLE I

Variables	**ADF**				
	Test Stat.	**Prob.**	**Lag**	**Max. Lag**	**n**
DAX	28,85	0.0000	0	24	1801
S&P500	32,74	0.0000	1	24	1800
NIKKEI	30,83	0.0001	0	24	1801
BIST100	30,79	0.0000	0	24	1801

GARCH (1,1) Models

Model table includes the result of garch model below.

DAX = 0,047 -0,1789*DAX(t-1) + 0,344*S&P500(t-1)]

+ 0,0082 + 0,0989*ARCH(1)+0,8818*GARCH(1)

NIKKEI = 0,0212 -0,1105*NIKKEI(t-1)]

+ 0,555*S&P500(t-1)+ 0,0128]

+ 0,113*ARCH(1)+0,862*GARCH(1)

BIST100 = 0,0428-0,076*BIST100(t-1)]

+ 0,599*S&P500(t-1)+ 0,0224]

+ 0,0679*ARCH(1)+0,903*GARCH(1)

TABLE II

Variables	05/01/2005-01/07/2014					
	Return Model			Variance Model		
	μ	γ_1	γ_2	ω	α_1	β_1
DAX	0,047*	-0,1789*	0,344*	0,0082*	0,0989*	0,8818*
NIKKEI	0,0212***	-0,1105*	0,555*	0,0128*	0,113*	0,862*
BIST100	0,0428**	-0,0763*	0,599*	0,0224*	0,0679*	0,9031*

***, **, *** shows %1, %5 ve %10 significance level. μ: return model constant; γ_1: each variables lag return; γ_2: S&P500 lag return; ω: variance model constant; α_1: arch coefficient; β_1: garch coefficient.**

The coefficients for each model were statistically significant.Comparing to the garch coefficients; for DAX model garch coefficient is 0,8818; for NIKKEI model garch coefficient is 0,862; for BIST100 model garch coefficient is 0,9031. For all periods; the biggest garch + arch coefficient is 0,980. Due to thisoutput; S&P500 has the biggest impact on DAX comparing to the NIKKEI and BIST100 stock markets.

Second higher garch + arch coefficient is 0,975. Due to the NIKKEI model; S&P500 has the second biggest impact on NIKKEI stock markets comparing to the BIST 100.

Lastly, for BIST 100 model;garch + arch coefficient is 0,971. Due to the BIST 100 model; S&P500 has the strong impact on BIST 100 stock market.

For all model arch+garch coefficients are less than 1. However, S&P500 stock market has strong impact on European and Asian stock markets. In case of any financial crisis, all stock markets are affected almost equally.

This graph shows the conditional variance of the garch model. Until the crisis period; NIKKEI stock market has most response to the S&P500.Secondly,until the crisis period; BIST 100 stock market has most response to the S&P 500. Lastly, until the crisis period, DAX has small response to the S&P500.

In crisis period (2008 and 009); comparing to the DAX and BIST100; NIKKEI stock has biggest response to the S&P500. It is around 6. Nikkei stock market seems to be more precise.

Comparing to the DAX and BIST 100 stock markets; NIKKEI has more sensitive on risk against S&P500.

BIST 100 has second biggest response to the S&P 500 in crisis period. It is around 5.

Lastly, DAX stock market has response to the S&P 500 in crisis period. It is around 4. Due to the garch model and conditional graph; S&P 500 stock market has impact all stock markets. After the crisis period the effects were continuing. In this case; NIKKEI has more sensivity risk against S&P500.

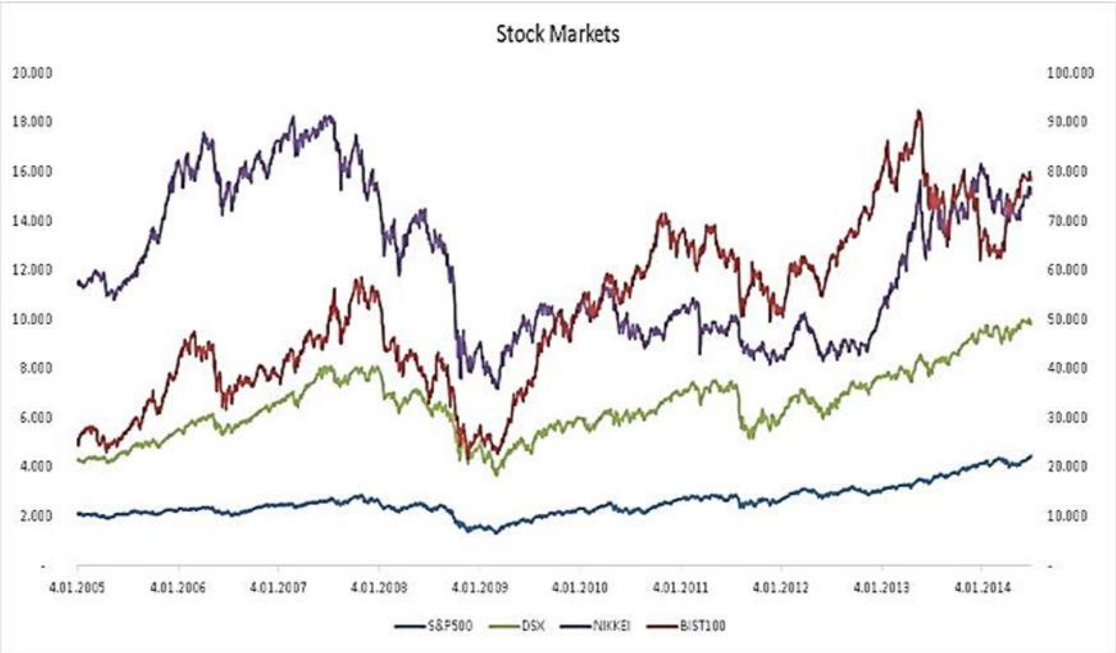

Fig. 1 Stock markets evolution

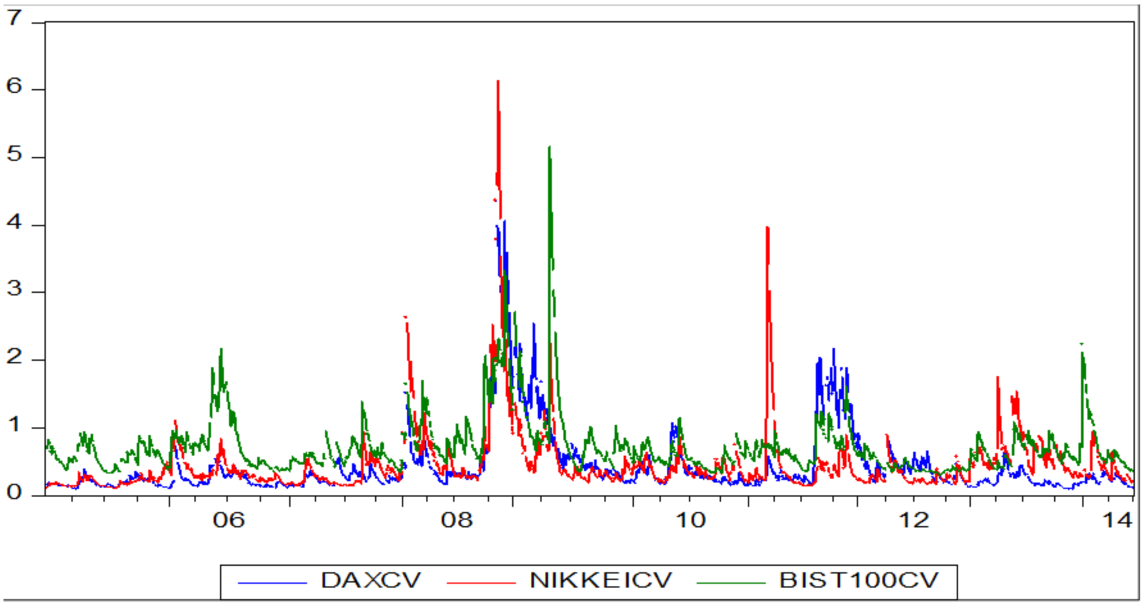

Fig. 2 Conditional Variance Evolution

Correlogram Analysis

Correlogram Table IIIshows correlogram analysis for DAX, NIKKEI and BIST 100 models. For all lag periods and models, prob values are greater than 0,05. In this case all models have not autocorrelation in their residual. Finallyall models are statistically significant.

TABLE III

CORRELOGRAM TABLE

	DAX		NIKKEI		BIST100	
Lag	**Q Stat.**	**Prob.**	**Q Stat.**	**Prob.**	**Q Stat.**	**Prob.**
1	0.1146	0.735	29160	0.088	0.1197	0.729
5	22.218	0.818	35.480	0.616	24.464	0.785
10	53.816	0.864	82.316	0.606	41.341	0.941
15	86.041	0.897	97.545	0.835	49.691	0.992

IV. RESIDUAL GRAPH

Residual graph shows for all models residual distribution between 2005 and 2014. Excluded crisis period, residual distribution is stationary. Between 2008 and 2010 residual of models were taken the highest value. Most important effect were at BIST 100 stock market. Comparing to the DAX and NIKKEI, BIST 100 is more sensitive to S&P 500 shocks. NIKKEI and DAX has equal sensitive to S&P 500 shocks. After crisis period BIST 100 and NIKKEI has equal sensitive to S&P 500 shocks. Comparing to the NIKKEI and BIST 100, DAX is as safe as houses.

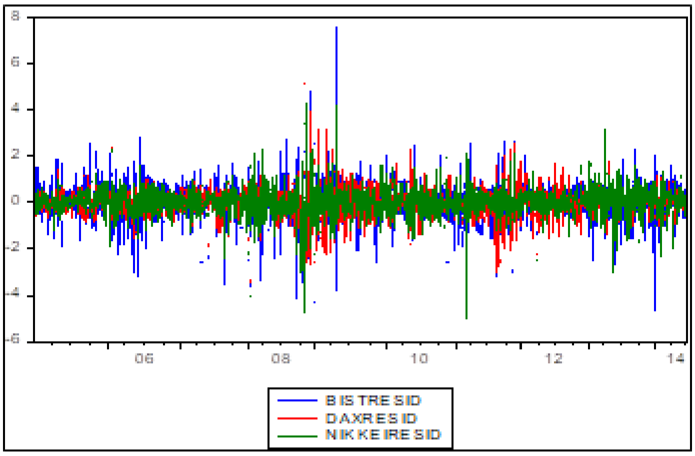

Fig. 3 Residual Graph

V. CONCLUSION AND DISCUSSION

Financial time series usually exhibit a set of characteristics. Stock market returns display volatility clustering where large changes in these returns tend to be followed by large changes and small changes by small changes, leading to contiguous periods of volatility stability. Generally, we are interesting in volatility modelling of the US stock index market.

ISSN: 2757-5519

The results of this study financial crises impact were analyzed in the stock market. As a result, the volatility on stock markets increased at crisis period. Before crisis period, volatility is stable. However due to the S&P500 changes, volatility is increased seriously at crisis period. Taking risk will bring big losses in that time. According to the crisis, it creates gateway for investors. In similar cases away from trust will not be easy. As shown, both European and Asian stock markets are deeply affected. This has happened all over the world. For further research, other financial instruments will be included in variance model therefore effects of other financial instruments can test in garch model.

REFERENCES

[1] N. A. Samarakoon, "Conditional Variance Function Checking in Heteroscedastic Regression Models" Paperback, Proquest, Umi Dissertation Publishing, 2012

[2] G. Gregoriou, "Stock Market Volatility", New York, Chapman and Hall/CRC; 1 edition, 2009

[3] S.Claessens, A. Kose, L. Laeven, F. Valencia, "Financial Crises: Causes, Consequences, and Policy Responses", Washington, International Monetary Fund, 2014

[4] M. Miller, "Mathematics and Statistics for Financial Risk Management", New Jersey, Wiley, 2 Ed. 2013

[5] R. Chatterjee, "Practical Methods of Financial Engineering and Risk Management : Tools for Modern Financial Professionals", New York, Springer, 2014

[6] C. Francq, "GARCH Models: Structure, Statistical Inference and Financial Applications", Wiley, 1 Ed. 2010

[7] L. Bauwens, C. Hafner, S. Laurent, "Handbook of Volatility Models and Their Applications", Wiley, 1 Ed. 2012