Volatility Spillover Effect With Time-Varying Parameters Between BIST100 and Dow-Jones Under Different Regimes

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Abstract

The aim of this study is to analyze the spillover effect of Dow-Jones index on BIST100 index under different regimes over the period of 01.01.2002-31.03.2017. We used weekly stock market returns relating to the mentioned stock markets. We obtain the volatility of so-called stock markets via GAS model which includes time-varying parameters. n the study, volatility spillover effect is examined using Markov Switching regression. Thus, we compare this effect for low volaitility regime and high volatility regime. It follows from the analysis that there is positive volatility spillover effect Dow-Jones to BIST100 under both regimes. However, the effect size is higher in low volatility regime than in high volatility regime.

Keywords: Volatility Spillover Effect, Markov-Switching Regression, GAS Model

Jel Codes: G15, G17, C34, C58

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INTRODUCTION

Liberalisation of capital flows, international trade and increases in investment in worldwide extinguish financial market bounds which are different geographically. Therefore, stock markets are affected by news announced in foreign countries. In other words, international stock markets become more dependent on each other (Lin et. al., 1994; Lupu, 2012). On the one hand emerging stock markets more and more grow, one the other hand they move in concert with developed stock markets, and so are more sensitive shocks from foreign countries. Especially the crisis when occured in United States in 2007 and in Europe in 2008 has made important determining the linkages between international stock markets. Within the frame of modern portfolio theory, stock market investments made from foreign stock markets can reduce portfolio risk to "global systematic risk" by balancing the risks in the country in contrast with domestic stock markets (Markowitz, 1952). In this regard, individual investors and fund managers must know comovements in international stock market to increase their income to gain from stock market investments. The risks exposed by investorscan decrease if the stock markets between which there are negative relationship are not correlated with each other (Hui, 2005).

Purpose of this study is to examine the connection between BIST100 index and Dow-Jones index under different regimes. Therefore, we exhibit how investors are protected from the risks between international stock markets in low volatility and high volatility. This study is contributed to the literature in two ways. Firstly, we investigate stock market volatility using GAS model. This model capture time-varying parameter based upon the score function of the estimated model in nonlinear model. This method makes use of high-dimensional covariance matrices and time-varying distributions. Second, the connection between so-called stock markets through Markov Switching regression. This model enable to compare the mentioned affect under low volatility and high volatility regimes.

LITERATURE REVIEW

There are wide range of the study examining the linkages between international stock markets in the literature. The primary studies in this area were generated by Grubel (1968), Granger and Morgenstern (1971), Levy and Sarnat (1970), Ripley (1973), Lessard (1974). The relationship in question in the literature have investigated via various methods such as multivariate GARCH, vector autoregressive model, cointegration analysis, spatial model.

Some of the studies discussing the international stock exchange linkages via cointegration analysis as follows: Kasa (1992) found that there are long-run relationship among the stock markets in United States, United Kingdom, Japon, Germany and Canada for 1974-1990. Ghosh et. al. (1999) showed the long-run relationship between Asian stock markets and US stock market. Narayan and Smyth (2005) revealed the long-run linkages between New Zeland and United States for 1967-2003. Bose and Mukherjee (2005) indicated that the stock markets in India was affected by the ones in Asia and United States over the period of 1999-2004.

As examined the study for Turkey in the literature, it is frequently seen to use cointegration analysis, vector error correction model and causality to reveal internation stock market linkages. Sevüktekin and Nargeleçekenler (2008) stated that Dow Jones, Nasdaq and S&P500 affect positively BIST100 for 1990-2001. Çelik and Boztosun (2010) investigated the linkages between Turkish stock market and Asian stock market via Johensen-Jelus cointegration test over the period of 1998-2009. It was found to be the long-run relationship between Turkish stock market and the stock markets in Singapure, Malesia, Taiwan and Kore, but not be valid so-called relationship for the stock markets in Japon, China, Hong-Kongi India, Australia and Indonesia. Bulut and Özdemir (2012) showed that there are long-run relationship between BIST100 and Dow Jones in 2001-2013.Samırkaş and Düzakın (2013) investigated the effect the stock markets of Eurasian countries on Turkey through Johansen cointegration test and stated not to be significant relationship between so-called markets for 1994-2012. Yıldız and Aksoy (2014) demonstrated that Morgan Stanley emerging market index and BIST100 comovement in the long-run and short-run in the result of vector error correction model over the period of 1990-2011. Using DCC-GARCH model, Hatipoğlu and Bozkurt (2014) indicated dynamic conditional correlation between Asia stock markets and Turkish stock market and the connections and volatilities between these markets change across time.

DATA AND METHODOLOGY

The aim of the study is to analysis whether volatility of Dow Jones Index affects volatility of BIST 100 Index. This is purpose, we used weekly data coveing the period 01.01.2002-31.03.2017. Firstly, we obtained stock market returns by using the formula as follows:

$$R_{it} = \log\left(\frac{P_{it}}{P_{it-1}}\right) (1)$$

where P_{it} is close prices of stock market index in period t. Descriptive statistics for returns relating to BIST 100 and Dow Jones Indexes are shown in Table 1. As seen Table 1, return of BIST 100 and its risk are greater than Dow Jones Index. According to Jarque-Bera statistics, the returns don't exhibit normal distribution. Their skewness and kurtosis values show that both series have leptucortic distribution.

Table 1: Descriptive Statistics

	RETURNBIST	RETURNDJ
Mean	0.001026	0.000360
Median	0.002298	0.001109
Maximum	0.111963	0.046460
Minimum	-0.083703	-0.086988
Std. Dev.	0.017632	0.009895
Skewness	-0.133862	-0.871512
Kurtosis	6.519568	12.01353
Jarque-Bera	409.5907	2770.766
Probability	0.000000	0.000000
Sum	0.809796	0.284026
Sum Sq. Dev.	0.244975	0.077152
Observations	789	789

We used GAS model so as to obtain stock market volatility. GAS model was suggested from Creal et. al. (2012). This model is new approach to observation-driver model and extentions to the models which have asymmetric, long memory, and other more complicated dynamics. Also, it involves generalized autoregressive conditional heteroskedasticity, autoregressive conditional duration, autoregressive conditional intensity, and Poisson count models with time-varying mean (Creal et. al., 2013).

Financial time series show some large changes such as jumps. Effects of jumps for financial returns have been modelled by Poisson or Bernoulli jump distribution. In some studies, it has been shown that jumps affect future volatility less than standard volatility models. Volatility models such as GARCH are assumed that future volatility is affectted similarly from shocks. But there are growing literature indicating that large returns affect future volatility less than smaller shocks.

Harvey and Chakrevarty (2008) and Creal, Koopman and Lucas (2012) independently proposed a novel way to deal with large returns in a GARCH context. These models depend on GARCH type equation fort he conditional variance obtained from the conditional score of the assumed distribution in regard to the second moment.

Let Nx1 vector y_t denote the dependent variable of interest, f_t the time-varying parameter vector, x_t a vector of exogenous variables, all at time t, and θ a vecctor of static parameters. Define $Y_t = \{y_1, \ldots, y_t\}$, $F_t = \{f_1, \ldots, f_t\}$ and $X_t = \{x_1, \ldots, x_t\}$. The available information set at time t consists of $\{f_t, F_t\}$ where $F_t = \{Y_{t-1}, F_{t-1} l, X_t\}$, for t= 1, …, n.

It is assumed that y_t is generated by the observation density $y_t \; p(y_t | f_t, F_t$. Furthermore, it is assumed that the mechanism for updating the time varying parameter f_t is given by the familiar autoregressive updating equation.

$$f_{t+1} = \omega + \sum_{i=1}^{p} A_i s_{t-i+1} + \sum_{j=1}^{q} B_j f_{t-j+1} (2)$$

where ω is a vector of constants, coefficient matrices A_i and B_j have appropriate dimensions for i=1, …, p and j=1, …, q, while s_t is an appropriate function of past data, $s_t = s_t(y_t, f_t, F_t; \theta)$.

The approach is based on the observation density for a given parameter f_t . When observation y_t is realizedd, time-varying f_t to the next periiod t+1 is updated with

$$s_t = S_t . \nabla_t , \nabla_t = \frac{\partial \ln p(y_t | f_t, F_t; \theta)}{\partial f_t} (3)$$

$$S_t = S(t, f_t, F_t; \theta)$$

where S(.) is a matrix function. Given the dependence of the driving mechanism in (2) on the scaled score vector (3), the equations (2)-(3) define the generalized autoregressive score model with orders p and q. We refer to the model as GAS(p,q) and we take p=q=1 (Creal, Koopman and Lucas, 2012).

EMPIRICAL RESULTS

We purposed to explain effects of volatility of Dow Jones Index on volatility of BIST 100 Index. Thus, we applied GAS model with time-varying parameters above-mentioned to obtain conditional variances. Table 2 shows the results of GAS model estimation for both returns.

Table 2: The Results of GAS Model Estimation

	BIST 100	Dow Jones
Constant x10^4	0.061830*	0.03915441**
	(0.036358)	(1.7695)
GAS (A_1)	0.061086***	0.161999***
	(0.020471)	(0.044291)
GAS(B_1)	0.978499***	0.955317***
	(0.013029)	(0.022397)
Student	6.691502***	7.322824***
	(1.6191)	(0.022397)
Diagnostic Tests		
Log Likelihood	2117.187	2644.822
Akaike	-5.349016	-6.686494
Schwarz	-5.307577	-6.645055
Q(10)	12.9432	8.80951
ARCH(10)	1.1579	1.5540

Note: *,** and *** respectively represent statistically significiants at levels of 0.10, 0.05 and 0.01

In the figure 1, the top panel represents the weekly continuously compoounded return from the BIST 100 between 2002 and 2017 and the estimated volatility. It has been seen that there are two big spike in volatility. The first of these was caused by terrorist attack in Istanbul of November 20, 2003. Other one was caused by 2008 global crisis.

Figure 1: Estimated Volatility, Score and Scaled Score for BIST 100

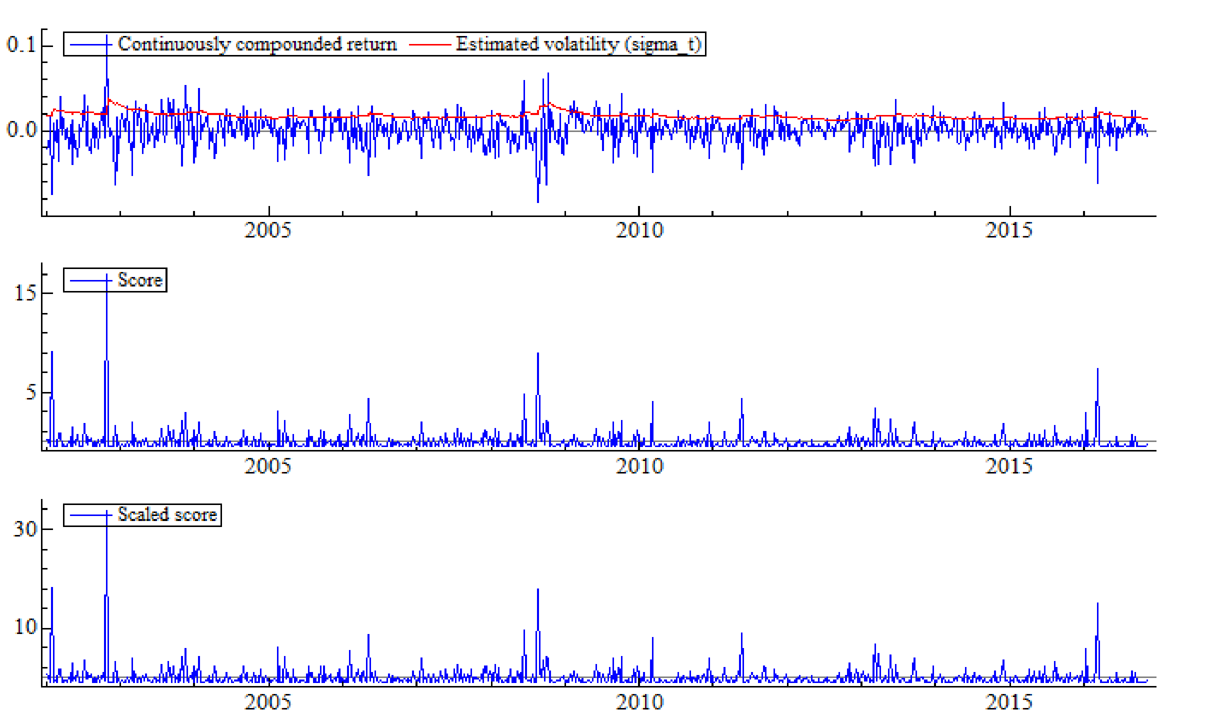


Figure 2: Comparison Between Gaussian and Student t Model for BIST 100

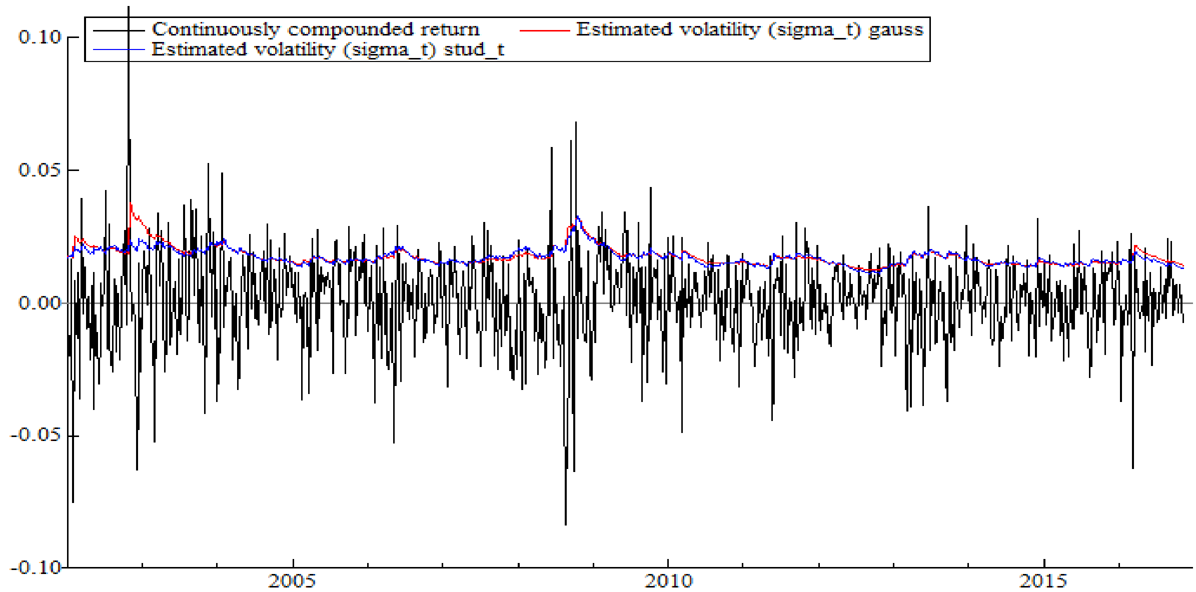
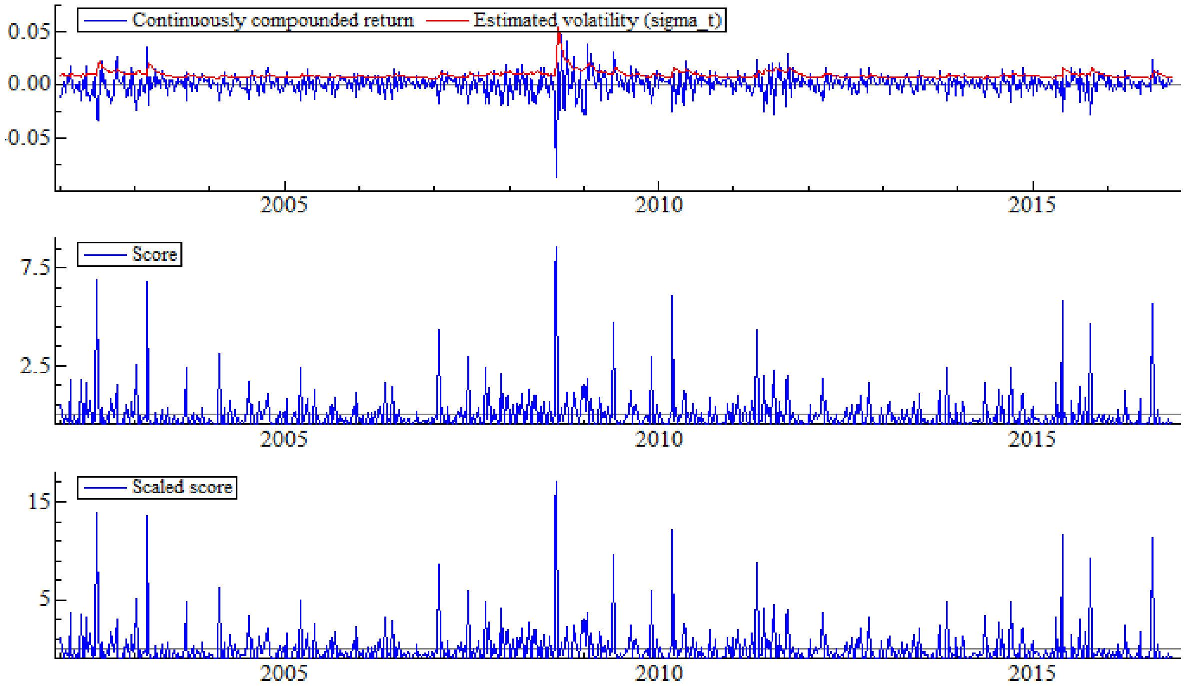


Figure 2 shows the weekly continuously compounded return from the BIST 100 between 2002 and 2017 and the estimated volatility by the Gaussian and the Student t model. The milder reaction of the Student t model to the terrorist attack in Istanbul of November 20, 2003 is clearly visible.

Figure 3: Estimated Volatility, Score and Scaled Score for Dow Jones



In the figure 3, the top panel represents the weekly continuously compoounded return from the Dow Jones between 2002 and 2017 and the estimated volatility. It has been seen that there are the big spike in volatility caused by 2008 global crisis.

Figure 4: Comparison Between Gaussian and Student t Model for Dow Jones

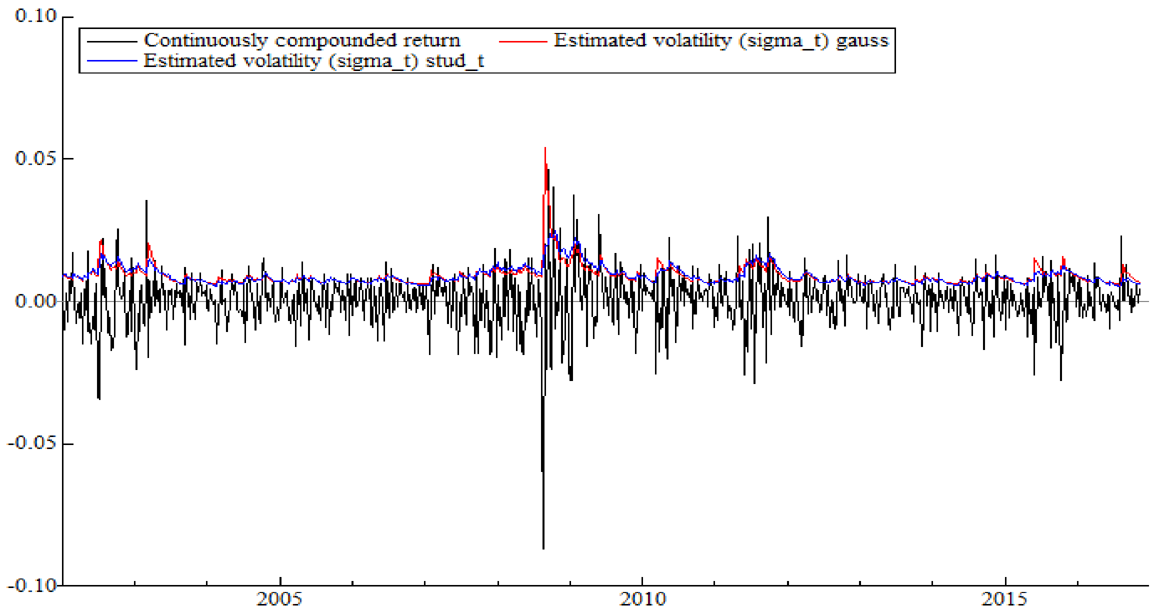
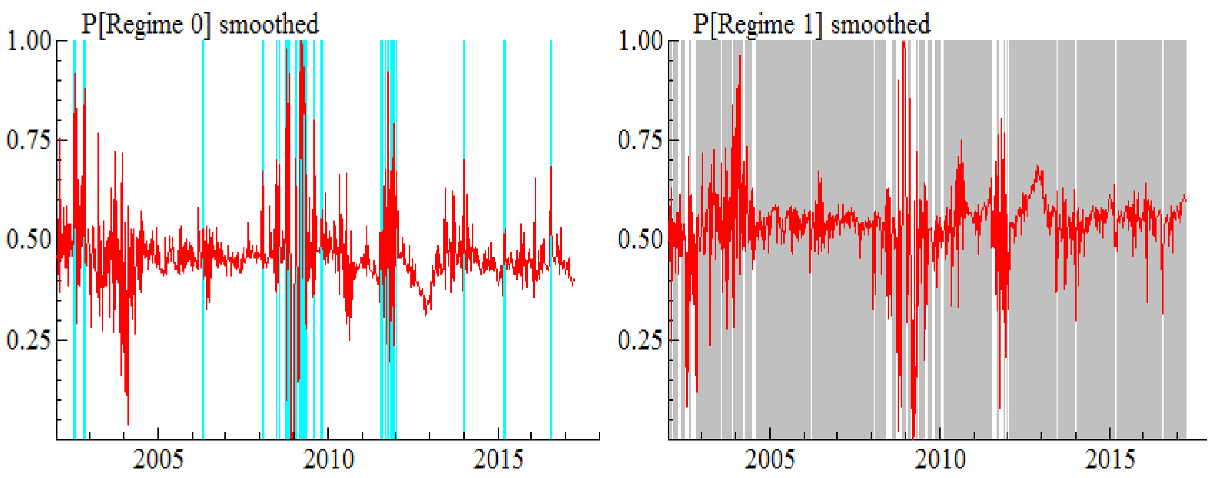


Figure 4 shows the weekly continuously compounded return from the Dow Jones between 2002 and 2017 and the estimated volatility by the Gaussian and the Student t model. The milder reaction of the Student t model to 2008 global crisis is clearly visible.

We applied Markov Switching approach so as to see how the effect of Dow Jones stock market volatility on BIST100 volatility change across different regimes. Therefore, we investigated so-called impact in bull and bear markets. We generated MS-ARMA(2,1,0,1) model. MS-ARMA(2,1,0,1) model estimation results are exhibit in Table 3 and regime properties are shown in Table 4. Also, the smoothed regime probabilities are seen in Figure 5.

Figure 5 Smoothed Regime Probabilities



As seen in Figure 5, regime 0 and regime 1 respectively state depression and expansion period of business cycle. On the other words, regime 0 represents high volatility regime and regime 1 represents low volatility regime.

Table 3 MS-ARMA(2,1,0,1) Model Estimation Results

Parameters	Coefficient	Standart Deviation
AR-1(0)	0.665785	0.03268***
AR-1(1)	0.815375	0.02898***
Constant(0)	0.000261101	1.196e-005***
Constant(1)	0.000233795	1.255e-005***
CondVDJ(0)	0.689109	0.06118***
CondVDJ(1)	0.965541	0.07414***
AIC	-17.7080676	
Log-likelihood	6986.97863	

Note: *** represents significance at 0.01 level.
0 and 1 values in the parenthesis respectively represent bear and bull market.
CondVDJ represents conditional volatility of Dow Jones stock market.

According to Table 3, the volatility of Dow-Jones index lead to the volatility of BIST100 index in both low volatility and high volatility regimes. In other words, there is positive volatility spillover effect from Dow-Jones to BIST100. As compared the effect size, it is seen that volatility spillover is higher in low volatility regime than in high volatility regime.

Table 4 reports regime properties relating to MS-ARMA(2,1,0,1) model.

Table 4 Regime Properties

	Regime 0, t+1	Regime 1, t+1	Observation	Duration (Months)
Regime 0, t+1	0.49804	0.49804	151	15.48
Regime 1, t+1	0.50196	0.50196	637	64.8

Examined regime transition probabilities, the transition probability from regime 0 to regime 0 and regime 1 equal to 0.49804. The transition probability from regime 1 to regime 0 and regime 1 equal to 0.50196. 151 observations are in regime 0 and 637 observations are in regime 1. Average duration in regime 0 and regime 1 respectively are 15.48 and 64.8 months.

CONCLUSION

In the study, we examined volaitility spillover effect from Dow-Jones index to BIST100 index 01.01.2002-31.03.2017 in terms of low volatility and high volatility regimes. We utilized from GAS model to generate time-varying dynamic conditional variance. We saw that there are two big spike in BIST100 (terrorist attack in 2003 and global financial crisis in 2008) while one big spike in Dow-Jones (global financial crisis in 2008). Using Markov Switching regression, we test volatility spillover effect between BIST100 and Dow-Jones under different regimes. It was inferred from the Markov Switching regression that there are positive volatility spillover effect between so-called stock markets. However, the mentioned effect is higher in low volatility regime than in high volatility regime. The results of the study indicated that the investors should make decision by monitoring developments in so-called countries because of risk transition between Dow-Jones and BIST100.

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