Journal of Applied Finance & Banking, vol. 5, no. 6, 2015, 37-50
ISSN: 1792-6580 (print version), 1792-6599 (online)
Scienpress Ltd, 2015

Asymmetry and Leverage Effect of Political Risk on Volatility: The Case of BIST Sub-sector

Güven Sevil[1], Melik Kamışlı[2] and Serap Kamışlı[3]

Abstract

Modelling volatility in financial asset prices is very important for investment decisions and risk management. It is known that, political risk has a negative effect on stock returns. Especially, markets in which political risk increased, investment decisions change based on the changes that occur in financial asset returns. On the other hand, investors react more to negative shocks than to positive shocks. In this context, for a healthy investment policy, it is very important to make decisions having regard to the variance breaks that occur because of the political risk. In the study, firstly, breaks in unconditional variance of Borsa Istanbul (BIST) sub-sector index returns are detected with Modified Iterated Cumulative Sums of Squares Method. In the sequel, political events are determined among all the events that cause breaks in variance. Finally, by using threshold autoregressive conditional heteroskedasticity (TARCH) model, it is tested that if political events that cause breaks in variance, cause asymmetry and leverage effect in volatility of sub-sector returns or not. According to the results, it is concluded that political risks that cause breaks in variance, cause asymmetry and leverage effect on return volatility of XKAGT, XTAST, XMANA and XMESY sub-sectors.

JEL classification numbers: G3, G11, P34
Keywords: Political Risk, Variance Break, Volatility, TARCH Model, Borsa Istanbul

1 Introduction

Volatility in asset prices affect investment decisions and portfolio management policies of investors based on changing risk. However, different types of shocks and crises that occur in financial markets in conjunction with the globalization, make difficult to determine and

---

[1]Anadolu University, *Open Education Faculty, Eskişehir, Turkey*.
[2]Corresponding Author: Bilecik Şeyh Edebali University, Bozüyük Vocational School, Department of Banking and Insurance, Bilecik, Turkey.
[3]Anadolu University, Social Sciences Institute, Eskişehir, Turkey.

Article Info: *Received :* August 2, 2015. *Revised :* August 31, 2015.
Published online : November 1, 2015

calculate risks properly. On the other hand, volatility can stem from the internal dynamics of markets based on the shocks caused by economic, political and social events, as it can stem from the other markets. Considering risks in conjunction with the events that change volatility provide important information to the investors about portfolio management. In this context, detecting breaks in variance is very important to calculate risk properly and for an efficient risk management.

While creating portfolio, some of the risks cannot be reduced with diversification. These risk factors are collected under the title of systematic risk and one of them is political risk. Political risk affect asset returns and the way of effect is generally negative. This risk type occur as a result of both national and international political events and it is higher in emerging countries than developed countries.

It is known that investors react more to negative shocks than to positive shocks. However, increase in the diversity of investment vehicles gives investors the opportunity of changing their positions. It is not possible that similar type of shocks affect different investment vehicles in the same durations. In this context, it will be healthier especially for the investors who create their portfolios with similar investment vehicles like stock indexes to designate their portfolio management policies bearing in mind the response durations of indexes to the political risks.

In the study, firstly, modified iterated cumulative sums of squares method which considers the heteroscedastic structure of financial times series, will be used in order to determine the breaks in unconditional variance By means of this method, events that cause breaks in the return variance of 18 sub-sector indexes of BIST Industrial (XUSIN), BIST Services (XUHIZ) and BIST Financial (XUMAL) sectors, will be determined. In the next step, events will be analyzed and political events will be detected among the events that cause breaks in variance. Finally, it will be tested with TARCH model that if political events cause asymmetry and leverage effect on return volatility or not and persistency levels of the shocks will be calculated.

2 Literature Review

Volatility modelling's most important result with regard to financial asset return is that volatility shocks are persistent. However, volatility persistence seems higher than it is, especially in models in which, breaks in unconditional variance are ignored. This situation leads to calculation of risk wrongly and cause investors to take wrong investment decisions. It is seen when the literature reviewed that, persistence is lower in the studies that consider breaks in variance while modelling volatility.

Lamoreux and Lastrapes (1990), Malik and Hassan (2004), Rapach and Strauss (2008), Marcelo et al. (2008) determined the breaks in unconditional variance by using different methodologies. In these studies, it is concluded that persistency of volatility decreases when sudden changes in returns are considered. However, there are different methods that consider breaks in variance while modelling volatility. Fernandez (2005), Fernandez and Lucey (2006) and Fernandez and Lucey (2007) used different methods to detect breaks in variance. The results of these studies are similar with the literature.

There are studies in the literature that take in to account breaks in variance while analyzing the financial markets of Turkey. Gursakal (2009) considered breaks in variance while modelling currency return volatility. Demireli and Torun (2010) observed breaks in variance while analyzing economic, political and social event that are thought to effect open market gold prices in Turkey and United Kingdom. Çağlı et al. (2012) used models that detect the variance breaks, while modelling BIST100 Index and Industrial, Services and Financial sector indexes. When all the studies are considered together, it is seen that volatility persistency decreases significantly, when sudden changes in return are taken into consideration.

Political risk causes changes in financial asset returns and it is shown by many studies in the literature. Chan and Wei (1996), Kim and Mei (2001) and Mei and Guo (2004) found that there is a negative relationship between political risk and stock prices. Aggarwal, Inclan and Leal (1999) considered breaks in variance and they found that emerging stock markets are effected from country-specific political events. Kaya et al. (2014) analyzed the impacts of political risk on Turkish stock market. According to the results, there is long-term relationship between political risk and stock prices and the direction of the relationship is negative. Çam (2014) investigated the effects of political risk on firm value and he showed that political risk affects firm value.

On the top of the studies focusing on the effects of political risk on stock returns, there are studies in the literature that analyze the effects of political risk on macroeconomic variables. Busse and Hefeker (2007) and Lensink, Hermes and Murinde (2000) studied on the effects of political risk on foreign capital investments and they indicated that there is a relationship between two variables. Alesina, Ozler, Roubini and Swagel (1996) and Şanlısoy and Kök (2010), analyzed the relationship between political instability and economic growth and in harmony with the literature, they found a reverse relationship between the variables. Arslan (2011) researched the relationship between political instability and gross domestic product (GDP) and he resulted that there is a long-term relationship between two variables.

Unexpected increases and decreases in financial asset returns cause asymmetric changes in volatility. In other words, in financial markets, the impacts of positive and negative shocks can differ from each other. The leverage effect in volatility modelling means that bad news have more effect on volatility than good news. Asymmetry means dissymmetrical effect of good and bad news on volatility. In this context, in the markets in which asymmetry and leverage effect exist, investors should change their portfolio management decisions if political risk occur. There are quite a few studies in the literature that analyze leverage and asymmetry effect for different markets.

Fabozzi, Tunaru and Wu (2004) calculated volatility of Shenzhen and Shanghai stock markets and they resulted that, the models which consider asymmetry and leverage effect are successful to analyze volatility dynamics. Goudarzi and Ramanarayanan (2011) determined asymmetry and leverage effect for Indian stock market. Özden (2008) modelled volatility of IMKB100 Index return and he indicated that the best model is the model which considers asymmetry and leverage effect. Akkün and Sayyan (2007) determined asymmetry in IMKB stock returns with asymmetric conditional heteroskedasticity models. Kıran (2010) investigated the relationship between trading volume and IMKB100 return volatility with different volatility models and he showed the asymmetry in return volatility.

When all the studies in the literature are considered together, it is seen that, it is necessary to determine breaks in variance in order to calculate risk properly. Besides that, it is clear that political risk has an important effect on stock returns. Therefore, in volatility modelling, determining the political risks that affect stock returns negatively, will present important information to investors. In this context, the aim of the study is to detect if political events that cause breaks in variance, cause asymmetry and leverage effect in volatility of BIST sub-sector index return or not and to calculate persistency levels of shocks.

3 Methodology and Data

The data set of the study consists of daily returns of BIST sub-sector indexes between 01.021997-11.03.2014. Sub-sectors of Industrial (XUSIN), Services (XUHIZ) and Financial (XUMAL) sectors are Food, Beverage (XGIDA), Wood, Paper, Printing (XKAGT), Chemical, Petroleum, Plastic (XKMYA), Basic Metal (XMANA), Metal Products, Machinery (XMESY), Non-Metal Mineral Product (XTAST), Textile, Leather (XTEKS), Electricity (XELKT), Telecommunication (XILTM), Sports (XSPOR), Wholesale and Retail Trade (XTCRT), Tourism (XTRZM), Transportation (XULAS), Banks (XBANK), Leasing, Factoring (XFINK), Real Estate Investment Trusts (XGMYO), Holding and Investment (XHOLD) and Insurance (XSGRT).

We used 4407 data of XGIDA, XKAGT, XKMYA, XMANA, XMESY, XTAST, XTEKS, 4304 data of XTCRT, XTRZM, XULAS, XBANK, XFINK, XHOLD, XSGRT, 4224 data of XELKT, 3592 data of XGMYO, 2458 data of XILTM and 2573 of XSPOR, because, the start dates of the indexes are different and indexes were closed in some days.

In the study, in compliance with our purpose, we used modified iterated cumulative sums of squares method, in order to detect breaks in unconditional variance of the series.

Inclan and Tiao (1994) introduced modified iterated cumulative sums of squares (ICSS) method to determine the breaks in unconditional variance of time series. The model was developed, in order to detect breaks in variance that occur because of the sudden shocks.

ICSS algorithm depends on IT test statistic that is derived from the use of sum of the squares of error terms;

$$IT = Sup_k \left|\sqrt{\frac{T}{2D_k}}\right| \tag{1}$$

Therefore, it can be seen from equation 1 that, ICSS algorithm depends on D_k statistic and the null hypothesis is as unconditional variance is constant.

$$D_k = \frac{C_k}{C_T} - \frac{k}{T}, \;\; D_0 = D_T = 0, \;\; k = 1,,,T \tag{2}$$

C_k, is the sum of cumulative squares of error terms under the assumptions of identical and independent processes and it is shown as follows;

$$C_k = \sum_{t=1}^{k} \varepsilon_t^2 \,, \;\; k = 1,,,T, \;\; \varepsilon_t \backsim iid\,(0,\sigma^2) \tag{3}$$

Null hypothesis is rejected and it is concluded that there is a break in variance if $Max_k\sqrt{\frac{T}{2D_k}}$ value is bigger than critical value.

In ICSS algorithm, IT test statistic depends on the assumption that error terms are distributed iid. But financial time series are generally heteroscedastic and distributed leptokurtic. Sanso et al. (2004) developed modified IT test statistic in accordance with the distribution properties of financial times series under definite assumptions, for the situations that error terms are not distributed iid.

$$k_2 = sup_k \left|\frac{1}{\sqrt{T}} G_k\right| \tag{4}$$

$$G_k = \frac{1}{\sqrt{\widehat{\omega}^4}}\left(C_k - \frac{k}{T} C_T\right) \tag{5}$$

In the study, political events that cause breaks are detected, after determination of the breaks in variance of BIST sub-sector index returns. In the next step, return volatility is modelled regardless of political risks. Finally, political events are included to the model as dummy variables and it is tested with TARCH model that if political risks cause asymmetry and leverage effect in return volatility or not.
Generalized autoregressive conditional heteroskedasticity (GARCH) model which is developed by Bollerslev (1986) is a volatility model that shows conditional variance depends on its own lagged values alongside of lagged values of error terms. As to threshold autoregressive conditional heteroskedasticity (TARCH) model proposed by Glosten, Jagannathan and Runkle (1993) is a model that shows the effects of negative and positive shocks on volatility are not symmetric. The conditional variance of TARCH model is given at equation 6;

$$h_t = \omega + \sum_{j=!}^{q} \beta_j \sigma_{t-j_t}^2 + \sum_{i=!}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{k=1}^{r} \gamma_k \varepsilon_{t-k}^2 I_{t-k}^- \tag{6}$$

In TARCH model, the effects of good news $(\varepsilon_{t-i} > 0)$ and bad news $(\varepsilon_{t-i} < 0)$ on conditional variance are different. I^- is dummy variable and it takes “1” value when $\varepsilon < 0$ and “0” value when $\varepsilon > 0$.
γ_k parameter which expresses leverage effect, indicates asymmetry if it is different than zero. There exists leverage effect if $\gamma_k > 0$. In other words, if $\gamma_k > 0$, bad news increase volatility more than good news. On the other hand, when there exists leverage effect, conditional variance is stationary if $\left(\alpha + \beta + \frac{\gamma}{2}\right) < 1$. In TARCH model the effect of good news is α_1 and the effect of bad news is $\alpha_1+\gamma_k$.
In the study, it is also aimed to be calculated persistency level of political shocks by calculation of half-life of shocks. Half-life of shock measures half-life of a shock to conditional variance in daily frequency. Half-life of shock is calculated as follows;

$$L_{half}=\ln\left(\frac{1}{2}\right)/\ln(\alpha+\beta) \tag{7}$$

4 Empirical Results

In the study, before, detecting breaks in variance and modelling volatilities, the graphics (Appendix – 1), stationary (Appendix – 2) and descriptive statistics of all BIST sub-sector index return series are analyzed.

Table 1: Descriptive Statistics of BIST Sub-sector Index Return Series

Descriptive Statistics of BIST-IND Sub-sector Index Return Series							
	XGIDA	**XTEKS**	**XKAGT**	**XKMYA**	**XTAST**	**XMANA**	**XMESY**
Mean	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Median	0.001	0.002	0.001	0.001	0.001	0.001	0.001
Maximum	0.183	0.178	0.159	0.187	0.170	0.198	0.177
Minimum	-0.192	-0.193	-0.165	-0.186	-0.176	-0.208	-0.186
Std. Dev.	0.024	0.023	0.026	0.025	0.020	0.029	0.026
Skewness	-0.226	-0.758	-0.251	-0.002	-0.257	-0.052	-0.178
Kurtosis	9.989	12.055	7.877	8.626	11.334	8.031	9.218
Jarque-Bera	9007.5*	15478.1*	4414.2*	5812.1*	12801.1*	4649.3*	7123.5*
LM(1)	649.7*	570.6*	408.6*	650.1*	755.2*	333.5*	646.5*
(5)	167.2*	166.9*	138.5*	183.8*	210.1*	122.7*	175.7*

Descriptive Statistics of BIST- SRV Sub-sector Index Return Series						
	DLXELKT	**DLXULAS**	**DLXTRZM**	**DLXTCRT**	**DLXILTM**	**DLXSPOR**
Mean	0.000	0.001	0.000	0.001	0.000	0.000
Median	0.000	0.001	0.000	0.001	0.000	0.000
Maximum	0.195	0.189	0.198	0.178	0.180	0.152
Minimum	-0.198	-0.183	-0.195	-0.204	-0.196	-0.204
Std. Dev.	0.029	0.028	0.032	0.025	0.028	0.021
Skewness	0.102	-0.028	0.201	0.038	0.043	-0.442
Kurtosis	9.321	7.377	8.795	10.492	9.736	13.851
Jarque-Bera	7039.9*	3435.7*	6050.6*	10068.1*	6537.8*	12706.9*
LM(1)	364,4*	348,7*	548,6*	372,8*	275,4*	44,6*
(5)	115,5*	93,1*	159,4*	169,1*	113,8*	28,1*

Descriptive Statistics of BIST- FIN Sub-sector Index Return Series					
	DLXBANK	**DLXFINK**	**DLXGMYO**	**DLXHOLD**	**DLXSGRT**
Mean	0.001	0.001	0.000	0.001	0.001
Median	0.001	0.000	0.001	0.001	0.001
Maximum	0.173	0.171	0.180	0.179	0.172
Minimum	-0.212	-0.184	-0.191	-0.202	-0.207
Std. Dev.	0.030	0.027	0.023	0.027	0.028
Skewness	0.107	-0.151	-0.170	-0.046	-0.130
Kurtosis	7.206	7.933	9.735	7.988	7.939
Jarque	3181.1	4380.5	6805.2	4463.0	4386.9
LM(1)	254,9*	377,7*	496,4*	390,6*	384,2*
(5)	88,6*	134,8*	139,8*	133,6*	144,4*

As it is seen from Table 1 that all of the BIST sub-sector index return series are not normally distributed according to skewness, kurtosis and Jarque-Bera statistics. However, all of the series have heteroscedasticity problem. Concordantly, in order to detect breaks in unconditional variance, modified iterated cumulative sums of squares method is used and break dates are given in Table 2.

Table 2: Break Dates in Unconditional Variance

<table>
<tr><th colspan="3">BIST-IND</th><th colspan="2">BIST-SRV</th><th colspan="2">BIST-FIN</th></tr>
<tr><td rowspan="3">XGIDA</td><td>03.19.2003</td><td>Second Gulf War</td><td rowspan="3">XELKT</td><td>12.07.2001</td><td rowspan="5">XBANK</td><td>09.08.2003</td></tr>
<tr><td>07.10.2008</td><td>Terrorism</td><td>07.06.2007</td><td>06.08.2004</td></tr>
<tr><td>02.24.2009</td><td>Political Party Crisis</td><td>09.17.2010</td><td>06.26.2007</td></tr>
<tr><td>XTEKS</td><td>04.15.2003</td><td>Second Gulf War</td><td>XULAS</td><td>04.14.2003</td><td>09.05.2008</td></tr>
<tr><td rowspan="2">XKAGT</td><td>04.03.2003</td><td>Second Gulf War</td><td rowspan="2">XTRZM</td><td>05.07.2003</td><td>12.01.2008</td></tr>
<tr><td>05.31.2010</td><td>Political Crisis with Israel</td><td>06.08.2009</td><td rowspan="6">XSGRT</td><td>03.24.2003</td></tr>
<tr><td rowspan="3">XKMYA</td><td>03.26.2003</td><td>Second Gulf War</td><td>XTCRT</td><td>04.09.2003</td><td>05.11.2006</td></tr>
<tr><td>01.10.2008</td><td>2008 Global Crisis</td><td rowspan="3">XILTM</td><td>03.21.2003</td><td>06.21.2006</td></tr>
<tr><td>02.20.2009</td><td>Agreement Between Government - Sector</td><td>09.18.2007</td><td>09.11.2008</td></tr>
<tr><td>XTAST</td><td>04.15.2003</td><td>Second Gulf War</td><td>03.05.2009</td><td>11.24.2008</td></tr>
<tr><td rowspan="5">XMANA</td><td>03.25.2003</td><td>Second Gulf War</td><td rowspan="2">XSPOR</td><td>09.22.2006</td><td>09.21.2011</td></tr>
<tr><td>01.15.2008</td><td rowspan="3">2008 Global Crisis</td><td>06.16.2008</td><td rowspan="2">XFINK</td><td>08.06.2004</td></tr>
<tr><td>09.08.2008</td><td rowspan="5" colspan="2"></td><td>12.08.2011</td></tr>
<tr><td>12.15.2008</td><td rowspan="3">XHOLD</td><td>03.25.2003</td></tr>
<tr><td>05.24.2010</td><td>Walkout</td><td>09.10.2008</td></tr>
<tr><td rowspan="2">XMESY</td><td rowspan="2">04.14.2003</td><td rowspan="2">Second Gulf War</td><td>11.25.2008</td></tr>
<tr><td>XGMYO</td><td>03.07.2006</td></tr>
</table>

When Table 2 is analyzed it is seen that there are more breaks in XMANA, XBANK and XSGRT sub-sector index returns. On the other hand, for BIST - IND sector index returns, it is concluded that the events that cause breaks in unconditional variance are generally associated with political risk. The events that cause breaks in unconditional variance of XUHIZ and XUMAL sub-sector index returns show similarity with BIST - IND sector index returns. But also there are different risks that cause breaks in unconditional variance of these indexes. In this context, in line with our purpose, we only modelled volatilities of BIST - IND sub-sector index returns.

The events that cause breaks in variance of BIST - IND sub-sector index returns are given in Table 2. It is detected that political risks that are related with internal dynamics of indexes cause breaks in variance alongside of international political events like Second Gulf War and 2008 Global Crisis.

In the next step, volatilities of BIST - IND sub-sector index returns are analyzed with TARCH model regardless of breaks in variance. ARCH-LM test is applied to residuals of models, in order to test ARCH effect. Also, Ljung-Box test is used to determine if there is autocorrelation in residuals.

Table 3: TARCH(1,1) Model without Dummy Variables

	XGIDA	XTEKS	XKAGT	XKMYA	XTAST	XMANA	XMESY
ω	0.0009*	0.0008*	0.0007*	0.0009*	0,0011*	0,0012*	0,0011*
α	0.129*	0.185*	0.141*	0.114*	0.187*	0.109*	0.111*
γ	0.018	0.058*	0.081*	0.034*	0.051*	0.034*	0.061*
β	0.841*	0.785*	0.809*	0.854*	0.779*	0.867*	0.856*
LM(1)	6,891*	0,908	2,299**	3,211	3,064**	2,688**	3,056**
(5)	2,503**	2,111**	1,485	1,067	1,7978	1,4995	1,621
Q(10)	3,026	55,84*	16,17	28,22*	12,71	10,18	7,19
(20)	6,676	75,34*	21,03	41,25*	25,74	18,62	10,29
Half Life of Shocks (Day)	22.8	22.8	13.5	21.3	20.0	28.5	20.7

*%1, **%5 Significance Level

Table 3 shows that, TARCH (1,1) models have heteroscedasticity and autocorrelation problems and coefficients are statistically insignificant. Therefore, in the next step of the study, volatility of industrial sub-sector returns are analyzed with TARCH model by adding political risks as dummy variables.

Table 4: TARCH(1,1) Model with Dummy Variables

	XGIDA	XTEKS	**XKAGT**	XKMYA	**XTAST**	**XMANA**	**XMESY**
d	0.032*	-0.015**	0.021**	0.037*	0.007*	0.011*	0.022**
ω	0.0009*	0.0008*	0.0007*	0.0009*	0,0011*	0,0012*	0.0009*
α	0.122*	0.183*	0.142*	0.115*	0.184*	0.109*	0.113*
γ	0.031*	0.057*	0.077*	0.037*	0.046*	0.036*	0.063*
β	0.841*	0.785*	0.809*	0.851*	0.784*	0.865*	0.853*
LM(1)	6,379**	0,9128	1,371	2,658	2,454	1,309	2,389
(5)	2,339**	2,121	1,707	0,927	0,911	0,418	0,641
Q(10)	3,436	55,67*	16,75	27,27*	13,52	9,72	8,22
(20)	7,415	74,97*	21,74	40,16*	27,85	18,16	12,55
$\alpha + \beta + \frac{\gamma}{2}$	0.979	0.997	0.990	0.985	0.991	0.992	0.998

*1%, **5% Significance Level

Table 4 shows the parameters of TARCH (1,1) model with dummy variables which represent breaks that are determined with modified iterated cumulative sums of squares method. All of the dummy variables are statistically significant and there is no heteroscedasticity and autocorrelation problem in TARCH model of XKAGT, XTAST, XMANA and XMESY at 5% significance level. All of the models satisfies $\left(\alpha + \beta + \frac{\gamma}{2}\right) < 1$ condition.

ARCH (α) parameter shows the short-term response of conditional variance to market shocks. According to the model results, XTAST has the highest α value. In this context, it can be said that volatility of XTAST sub-sector index return is more sensitive to market conditions. GARCH (β) parameter shows the long-term persistency in conditional variance independently of market conditions. So, it can be said that, it will take along time for disappearance of volatility of XMANA sub-sector index return.

If γ_i parameter, which is in the volatility model of XKAGT, XTAST, XMANA and XMESY sub-sector index returns, is different from zero, it means that the effect of political risks and positive events are different. On the other hand, all of the γ_i parameters in the models are bigger than zero and it shows that, the effect of political risk on volatility is bigger than the effect of positive events. In other words, political risks have asymmetry and leverage effect on volatility of XKAGT, XTAST, XMANA and XMESY sub-sector index returns. The effect of political risks and positive events on conditional variance is given in Table 5.

Table 5: The Effect of Political Risks and Positive Events on Conditional Variance

	XKAGT	**XTAST**	**XMANA**	**XMESY**
Positive Events (α)	0.142	0.184	0.109	0.113
Political Risks ($\alpha_1+\gamma_k$)	0.219	0.23	0.145	0.176

Half-lives of shocks are given in Table 6.

Table 6: Half-lives of Shocks

XKAGT	XTAST	XMANA	XMESY
13.8	21.3	26.3	20

When Table 6 is analyzed it is seen that, half-lives of shocks for XKAGT, XTAST, XMANA and XMESY index returns are less than one month. The sector which has the highest half-life of shock is XMANA with 26 days. In this context, it can be said that, investors who are willing to invest in industrial sub-sectors, should consider persistency of shocks and asymmetry and leverage effect of political risk while they give short-term purchase and sale decisions.

5 Conclusion

In the study, in which asymmetry and leverage effects on return volatility are analyzed, first of all, breaks in unconditional variance of BIST sub-sector index returns are detected. Results indicates that, Second Gulf War and 2008 Global Crisis effected almost all of the selected sub-sector indexes. The other shocks that cause breaks in variance generally develop out of sector-specific events. It is also seen that, the events that cause breaks in unconditional variance of Industrial sub-sector indexes are generally associated with political risks and there are more breaks in XMANA, XBANK and XSGRT sub-sectors than the others.

While modelling volatility of industrial sub-sector index returns, political risks are taken as basis in accordance with the aim of the study and it is tested that if political risks cause asymmetry and leverage effect or not. According to the results, political risks cause asymmetry and leverage effect on volatility of XKAGT, XTAST, XMANA and XMESY sub-sector index returns. In other words, political risks have more effect on volatility of XKAGT, XTAST, XMANA and XMESY sub-sector index returns, than positive events. In this context, political events should be observed attentively when political risks increase because of the asymmetric structure of industrial sub-sector index returns. Persistency of shocks are short-term. The half-lives of shocks for XKAGT, XTAST, XMANA and XMESY index returns are less then one month. Also it is resulted that volatility of XTAST sub-sector index return is more sensitive to market conditions. Therefore, risk-sensitive investors should refrain from short-term purchase and sale when sudden changes occur in the market. However, short-term asymmetry gives opportunity of high return to the investors who are risk-seeking.

When all the results are considered together, it can be said that, investors who want to invest in BIST, should care the breaks in variance and political risks. Political risks have short-term effects on BIST industrial index returns. Therefore, investors who want to invest in industrial sub-sectors, should take into consideration political risks, in short-term investment decisions, risk management and value at risk calculations. For a further study, the study can be replicated as considering interactions between financial markets and with a data set that includes different investment vehicles.

References

[1] R. Aggarwal, C. Inclan, and R. Leal, "Volatility in Emerging Stock Market," *The Journal of Financial and Quantitative Analysis*, **34**, 1, 1999, pp. 33-35.

[2] I. Akkün and H. Sayyan, "İMKB-30 Hisse Senedi Getirilerinde Volatilitenin Kısa ve Uzun Hafızalı Asimetrik Koşullu Değişen Varyans Modelleri ile Öngörüsü," *İşletme, İktisat ve Finans Dergisi*, **22**, 250, 2007, pp. 127-141.

[3] A. Alberto, S. Ozler, N. Roubini and P. Swagel, "Political Instability and Economic Growth," *Journal of Economic Growth*, **1**, 2, 1996, pp. 189-211.

[4] Ü. Arslan, "Siyasi İstikrarsizlik ve Ekonomik Performans: Türkiye Örneği," *Ege Akademik Bakış*, **11**, 1, 2011, pp. 73-80.

[5] T. Bollerslev, "Generalized Autoregressive Conditional Heteroskedasticity," *Journal of Econometrics*, **3**1, 1986, pp. 307-327.

[6] M. Busse and C. Hefeker, "Political Risk, Institutions and Foreign Direct Investment," *European Journal of Political Economy*, **23**, 2007, pp. 397-415.

[7] J. C. Cosset and J. M. Suret, "Political Risk and the Benefits of International Portfolio Diversification," *Journal of International Business Studies*, **26**, 2, (1995), pp. 301-318.

[8] Y. Chan and K. C. J. Wei, "Political Risk and Stock Price Volatility: The Case of Hong Kong," *Pacific Basin Finance Journal*, **4**, 1996, pp. 259-275.

[9] E. Ç. Çağlı, P. E. Mandacı and H. Kahyaoğlu, "Volatility Shifts and Persistence in Variance: Evidence from the Sector Indices of Istanbul Stock Exchange," *International Journal of Economic Sciences and Applied Research*, **4**, 3, 2012, pp. 119-140.

[10] A. V. Çam, "The Relationship between Political Risk and Firm Value: An Application on Companies In ISE," *Doğuş Üniversitesi Dergisi*, **15**, 1, 2013, pp. 109-122.

[11] J. Danielsson, "Financial risk forecasting: the theory and practice of forecasting market risk with implementation in R and Matlab," Wiley-Blackwell, 2011.

[12] E. Demireli and E. Torun, "Alternatif Piyasa Oynaklıklarında Meydana Gelen Kırılmaların ICSS Algoritmasıyla Belirlenmesi ve Süreğenliğe Etkileri: Türkiye ve Londra Örneği," *Muhasebe ve Finansman Dergisi*, **46**, 2010, pp. 129-145.

[13] F. J. Fabozzi,, R. Tunaru and T. Wu, "Modeling Volatility for Chinese Equity Markets," *Annals of Economics and Finance*, **5**, 2004, pp. 79-92.

[14] V. Fernandez, "Structural Breakpoints in Volatility in International Markets," Institute for International Integration Studies (llIS) Discussion Paper, No. 76, 2005, Dublin.

[15] V. Fernandez and B. Lucey, "Portfolio management implications of volatility shifts: Evidence from simulated data," Institute for International Integration Studies (llIS) Discussion Paper, No. 131, 2006, Dublin.

[16] V. Fernandez, "Stock Market Turmoil: Worldwide Effects of Middle East Conflicts," *Emerging Markets Finance and Trade*, **43**, 3, 2007, pp. 58-102.

[17] L. R. Glosten, R. Jagannathan and D. E. Runkle, "On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks," *The Journal of Finance*, **48**, 5, 1993, pp. 1779-1801.

[18] H. Goudarzi and C. S. Ramanarayanan, "Modeling Asymmetric Volatility in the Indian Stock Market," *International Journal of Business and Management*, **6**, 3, 2011, pp. 221-231.

[19] S. Gürsakal, "Varyans Kırılması Gözlemlenen Serilerde Garch Modelleri: Döviz Kuru Oynaklığı Örneği," *Erciyes Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*, **32**, 2009, pp. 319-337.

[20] S. Hammoudeh and H. Li, "Sudden Changes in Volatility in Emerging Markets: The case of Gulf Arab Stock Markets," *International Review of Financial Analysis*, **17**, 2008, pp. 47-63.

[21] C. Inclan and G. C. Tiao, "Use of Cumulative Sums Of Squares for Retrospective Detection of Changes of Variance," *Journal of the American Statistical Association*, **89**, 427, 1994, pp. 913-923.

[22] A. Kaya, B. Güngör and M. S. Özçomak, "Politik risk yatırımcının dikkate alması gereken bir risk midir? Borsa İstanbul örneği," *Gazi Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*, **16**, 1, 2014, pp. 74-87.

[23] H. Y. Kim and J. P. Mei, "What Makes The Stock Market Jump? An Analysis of Political Risk on Hong Kong Market Returns," *Journal of International Money and Finance*, **20**, 2001, pp. 1003-1016.

[24] C. G. Lamoureux and W. D. Lastrapes, "Persistence in Variance, Structural Change, and the GARCH Model," *Journal of Business & Economic Statistics*, **8**, 2, 1990, pp. 225-234.

[25] R. Lensink, N. Hermes and V. Murinde, "Capital Flight and Political Risk," *Journal of International Money and Finance*, **16**, 2000, pp. 73-92.

[26] F. Malik and S. A. Hassan, "Modeling Volatility in Sector Index Returns with GARCH Models Using an Iterated Algorithm," *Journal of Economics and Finance*, **28**, 2, 2004, pp. 211-225.

[27] J. L. M. Marcelo, J. L. M. Quirós, and M. D. M. M. Quirós, "Sudden shifts in variance in the Spanish market: persistence and spillover effects," *Applied Financial Economics*, **18**, 2008, pp. 115-124.

[28] J. Mei and L. Guo, "Political Uncertainty, Financial Crisis and Market Volatility," *European Financial Management*, **10**, 4, 2004, pp. 639-657.

[29] Ü. H. Özden, "İMKB Bileşik 100 Endeksi Getiri Volatilitesinin Analizi," *İstanbul Ticaret Üniversitesi Sosyal Bilimler Dergisi*, **7**, (13), 2008, pp. 339-350.

[30] D. E. Rapach, J. K. Strauss and M. E. Wohar, (2007), "Forecasting Stock Return Volatility in the Presence of Structural Breaks", In: D. E. Rapach and M. E. Wohar (Ed.) Forecasting in the Presence of Structural Breaks and Model Uncertainty, Emerald Group Publishing, 2007.

[31] A. Sansó, V. Aragó and J. L. Carrion, "Testing for change in the unconditional variance of financial time series," *Revista de Economia Financiera*, **4**, 2004, pp. 32-53.

[32] S. Şanlısoy and R. Kök, "Politik İstikrarsızlık Ekonomik Büyüme İlişkisi: Türkiye Örneği (1987-2006)," *Dokuz Eylül Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*, **25**, 1, 2010, pp. 101-125.

[33] R. S. Tsay, "Analysis of Financial Time Series," John Wiley&Sons, Inc., 2002.

[34] S. Yoon, K. S. Lee, "The Volatility and Asymmetry of Won/Dollar Exchange Rate," *Journal of Social Sciences*, **4**, 1, 2008, pp. 7-9.

Appendix

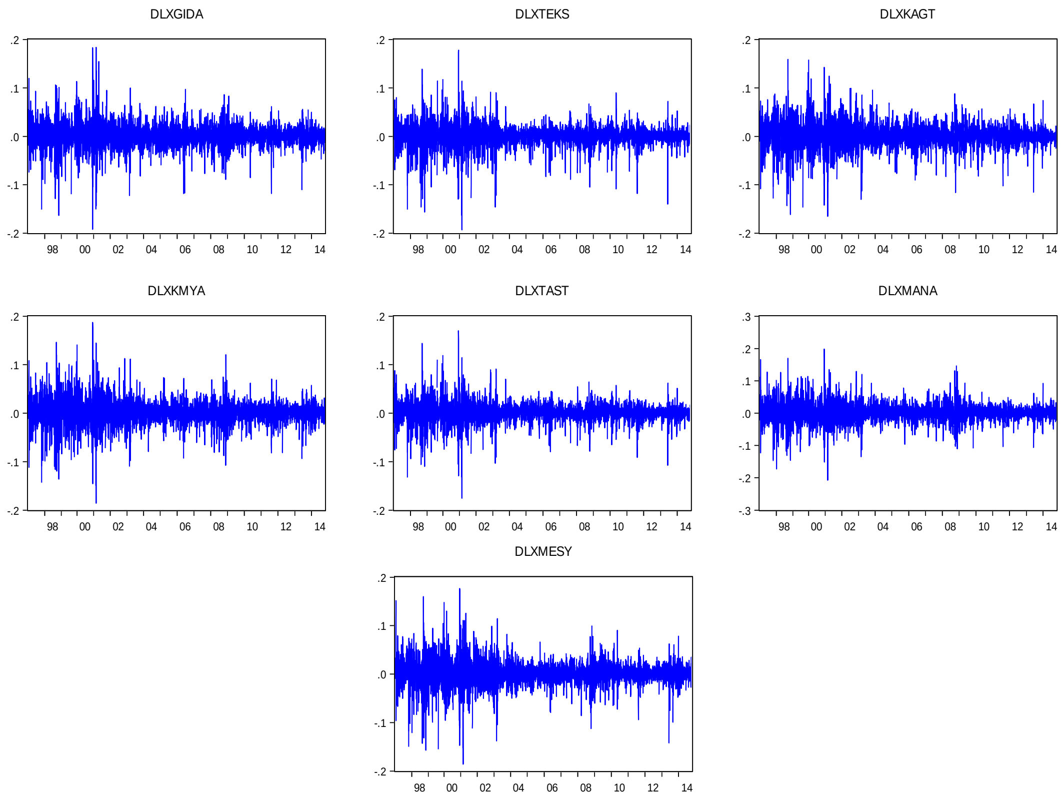

Figure 1: The Graphs of Industrial Sub-sector Index Returns

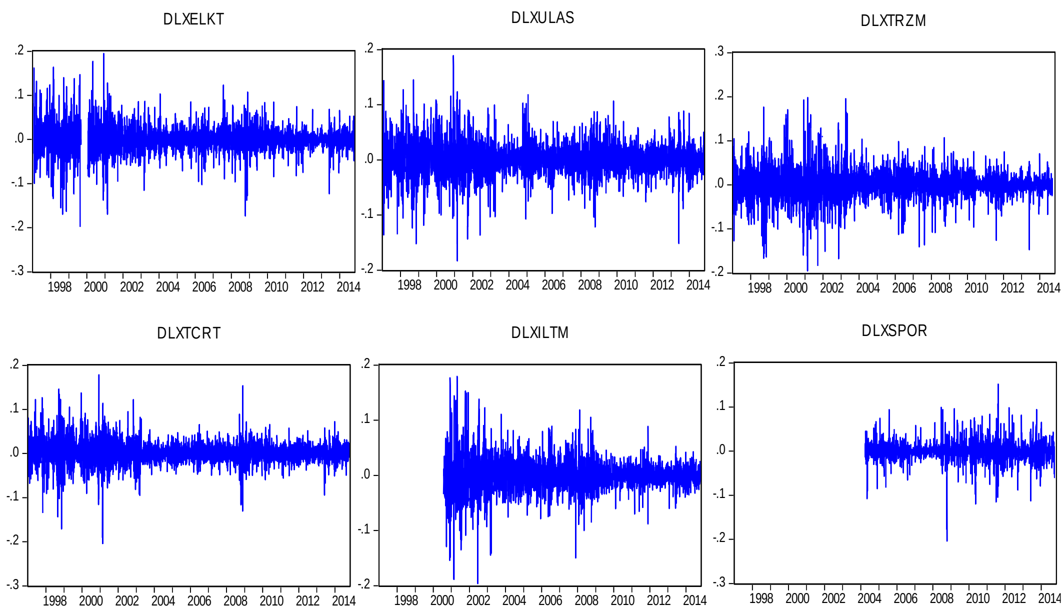

Figure 2: The Graphs of Services Sub-sector Index Returns

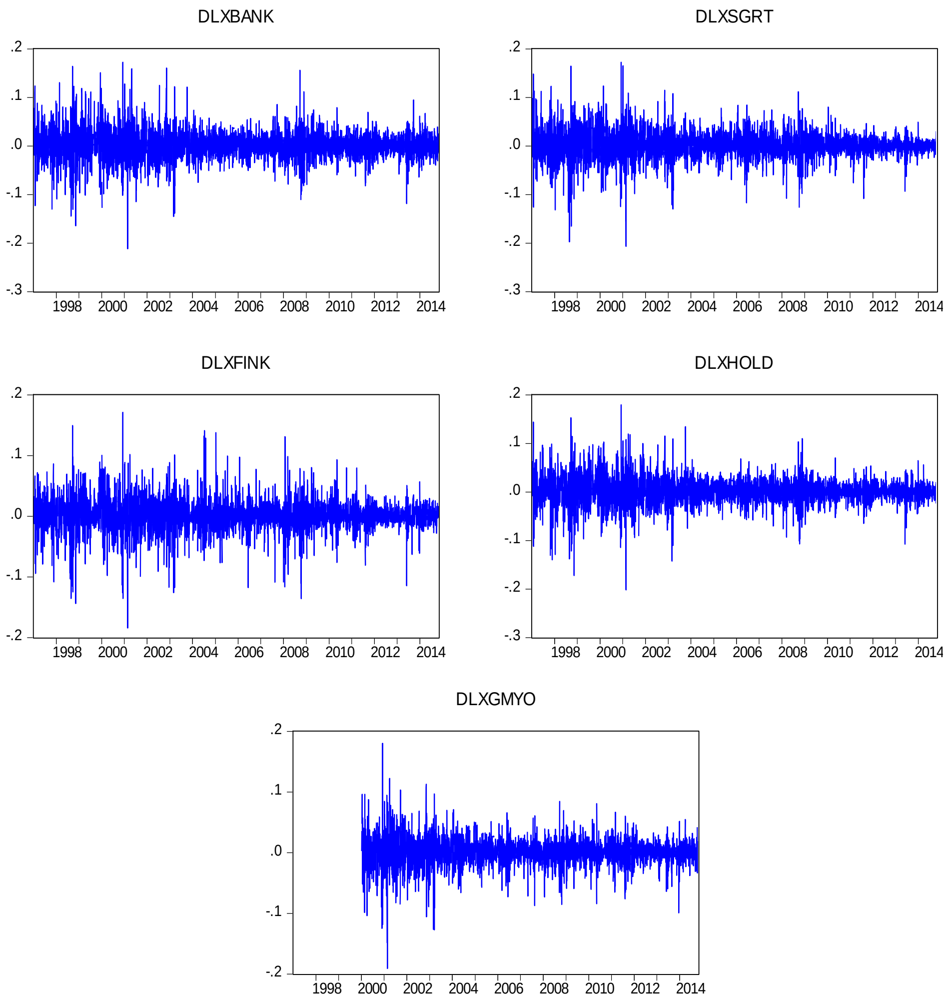

Figure 3: The Graphs of Financial Sub-sector Index Returns

Table A1: Unit Root Tests of Industrial Sub-sector Index Return Series

	ADF
	Level
DLXGIDA	-66.24615*
DLXTEKS	-61.72251*
DLXKAGT	-64.06808*
DLXKMYA	-66.01480*
DLXTAST	-63.23306*
DLXMANA	-65.78301*
DLXMESY	-63.25297*

*H_0 is rejected at %1