Global Journal of Business, Economics and Management

Volume 07, Issue 1, (2017) 178-197

www.wjbem.eu

Analyzing the leverage effect in stock indexes with autoregressive generalized variance models

Ilhami Karahanoglu[1]**,** Faculty of Economics and Business, Development Bank of Turkey, Izmir Cad. No 35 Kizilay Cankaya, Ankara, Turkey.

Harun Ercan, Department of Finance, Faculty of Business Administration, Corvinus University of Budapest, Financial Research Center, Fovam ter 8, 1093 Budapest, Hungary.

Suggested Citation:

Kahramanoglu, I. & Ercan, H. (2017). Analyzing the leverage effect in stock indexes with autoregressive generalized variance models. *Global Journal of Business, Economics and Management: Current Issues. 7*(1), 178-197.

Received November 19, 2016; revised January 7, 2017; accepted March 20, 2017;

Selection and peer review under responsibility of Prof. Dr. Andreea Iluzia IACOB, Bucharest Academy of Economic Studies, Romania.

Abstract

In developing and developed economies understanding the movement of stock market is extremely important to understand the riskiness of the investment, general behavior of the economy and taking the right position against the forthcoming financial events. In this study, the volatility of Turkish, Brazilian, German, London and New York Stock Indices are analyzed with ARCH type of modeling and the leverage effect is researched for the period between 04.01.2011 to 26.05.2015. There are two interesting results of this study. Firstly; it was seen that in all of those stock markets there is a leverage effect which means the negative movement in volatility is stronger than the positive one. Secondly the general structure of the ARCH type of modeling which explains the leverage effect shows similarity between those developed and developing markets.

Keywords: GARCH, TGARCH, leverage, stock exchange.

[1]* ADDRESS FOR CORRESPONDENCE: **Ilhami Karahanoglu,** Development Bank of Turkey, Izmir Cad. No 35 Kizilay Cankaya, Ankara, Turkey. *E-mail address*: Ilhami.Karahanoglu@kalkinma.com.tr

1. Introduction

Following the stock market data, is not only important for optimizing the current portfolios, but also to get an idea about the general and forthcoming situation of the economies itself. It is a very well tool for the fresh construction of portfolios too. It is both a pioneer for the investors both from profit and risk perspective. In addition, the β coefficient of CAPM which is used by active and the passive strategies is extremely important. Considering those, the following of the stock market change and is relationship with the portfolios itself is vital Literman (2008). At that very point it would not be very wrong to emphasize that the price and risk followers use the different methodologies. The price analysts prefer the more deterministic models to explain the price movements whereas the risk analysts are into volatility (Jorion & Zhang, 2008). As one of the most important variable for the risk measurements is volatility, (which is defined as a measure that is used to quantify the amount of variation or dispersion of a set of data values from is mean). Under the condition where the standard deviation and volatility is high the expected value which is he weighted average of the returns would functions with higher risk. So, the understanding or measurement of volatility of the stock indices are extremely important for understanding the risk for the return for those stock market and as well as the risk in the current economies.

As it is well defined above concentrating only on the last prices of investment product or just using the time series analysis for such product would be extremely wrong and non-coherent strategy. So in order to overcome such a shortcoming of volatility has been used as a predictive or informative variable for the investment strategies. Hence volatility can be used as a tool for the purifying the strategies and as well as creating the visions (Angelidis, Benos & Degiannakis, 2004). Although volatility is accepted as a non-changing term in most of the studies, in recent years it is seen that it is changing and more than this it can be modelled. Moreover, it is stated by many researchers that the low volatility session is followed by the low volatility and high volatility sessions are followed by the high volatilities (Karahanoglu & Ercan, 2016). By looking at the daily return of the 5 developing and developed countries stock returns, the volatility clustering can be seen easily. Mandelbrot (1963) was one of the first researchers who stated that the volatility could be modelled. However the model which estimates the volatility was constructed by the Nobel Prize winner Engel (1983), and Boleslav (1986). Such valuable studies are followed and supported by Nelson and Cao (1992)

In this research, the volatility of the Stock exchange markets namely Turkish, Brazil (developing countries), USA, Germany and UK (as developed countries) is modelled with well-known ARCH and GARCH (1, 1) process between 2011 and 2016. Moreover in order to measure the effect of leverage (which means the negative TGARCH families are used. At the last part all those 5 markets are compared based upon the results of ARCH, GARCH and TGARCH models.

2. Literature Review

Studies examining the BIST (BorsaI Istanbul- Turkish Stock Exchange) volatility have not revealed any research focused on the sub-indices so far. Although there are securities available derived from BIST30, derivatives of the other sub-indices have not started to be traded yet. The researches on the volatility of the BIST 100 index were not abundant.

Chou (1988) have demonstrated markets in the study describing that volatility persistence and risk premiums in the securities that IGARCH type models are quite effective in order to see the depth of the impact of price volatility.

Karolyi (1995) modelled the short term volatility changes in New York and Toronto markets and have demonstrated the differences by GARCH model showing continuity at the point of detection.

Frances and Van Dijk (1998) have surveyed a volatility analysis in the stock markets of 5 different countries. They pointed out that GARCH is more effective than GJR modeling, in addition to this, during the periods the extreme values are not experienced, QGARCH is suggested to be the best predictive model.

Speigh, and Gwilym (2000) EGARCH is suggested as a better tool to estimate the volatility of the stock market index due to it is more effective than GARCH model. This view is supported by the findings reached by Ederingto and Guan (2005)'s research.

Corradi and Avarta (2005), asserted that GARCH family can be used to estimate the non-sampling volatility elements the and they resulted that the most appropriate GARCH model would be GARCH (1,1).

Marucci (2005), in his study, revealed that GARCH models are inadequate for volatility forecasting for different periods (Daily, Monthly) with high and low frequency volatility periods, and the MRS-GARCH models produce more accurate solutions.

Kumar (2006) has observed unstable volatility in Indian stock exchange market and the GARCH (5,1) is suggested as the best forecasting model of the volatility. In addition; Goudarzi and Ramayanar (2011) also investigated the presence of asymmetric volatility in the same market and have modeled the asymmetric volatility most effectively with TAGRCH.

Alberg, Shalit and Yosef (2008) studied the mean return and conditional variance of Tel Aviv Stock Exchange (TASE) indices by using various GARCH models. Their findings supported that asymmetric GARCH model with fat-tailed densities improves overall estimation for measuring conditional variance. The EGARCH model using a skewed Student-t distribution is the most successful for forecasting TASE indices.

Du, Cindy and Hayes (2011) have investigated negative speculative operations on the stock market indices and they suggested that such speculation is related with the leverage in volatility.

Almeida and Hotta (2014) used asymmetric Garch family models because traditional models failed to explain the asymmetry of the distribution of errors and the leverage effect. Their results suggested that under the VaR estimation, the models with asymmetric errors perform much better than those with symmetric distributions.

Ozden (2008) modeled the index volatility of the BIST100 by following the daily returns occurred between the years 2000 to 2008 by ARCH and GARCH family and suggested T-GARCH (1, 1) as it presents the best results.

Atakan (2008) has completed the same research in a longer period (1987-2008) and the volatility could be modelled by GARCH (1, 1).

Demir and Cene (2012), in their study which focuses on the index BIST100, has succeeded in modeling volatility of the index values occurred between 2002-2011 by using ARCH (1,1) model.

Kutlar and Torun (2013), in their research focused on the BIST100 index and the index volatility is modelled with the help of GARCH family. They suggested that T-GARCH (1,1) provides the best solutions.

Karabacak, Mecik and Genc (2014) have used many alternatives of the GARCH family in their study. BIST100 index is accepted as an investment instrument left and T-GARCH (1, 1) was able to model the most effectively volatility of the yields between the period 2011 and 2013. Also they demonstrated in the study that the return value has an asymmetrical impact on volatility.

As it can be resulted from this literature review, different researchers have accepted that the yield volatility of BIST100 index is unstable and the volatility of the residual value in the different time series were modeled with the assistance of the GARCH family, and mostly T-GARCH (1,1) and GARCH (1, 1).

3. Methodology

Autoregressive Conditional Heteroskedasticity (ARCH) and Generalized Autoregressive Conditional Heteroscedasticity (GARCH)

Due to its autoregressive structure on conditional variance, ARCH, allows the volatility shocks to persist over time. This persistence captures the propensity of returns of like magnitude to group in time and can clarify the non-normality and non-stability of distributions of empirical asset returns (Fama, 1965).

Adoption of squared residuals of the model error term in time series or in linear model has not changed during data set is named as homoscedastic. However, as shown above, these error terms, especially in financial data sets may change periodically. In this sense, error terms with nonstable volatility in financial data follows a heteroskedastic process and this variability can be modelled. It is precisely at this point, a structure heteroskedastic ARCH-GARCH family has been demonstrated to be model this volatile structure.

Engle (1982) expressed the error terms which has the mean "0" in a stochastic process and has acted on the assumption that there is no correlation between these terms. This conditional variance depends on not only the square of the error term but also conditional delayed variance.

$$\varepsilon_t^2 = Z_t * \sqrt{h_t}$$

As shown above, the error term, with the mean "0" with variance 1 indicates a normal distribution. White noise process, h (t) also shows that the time-dependent conditional variance. T represents the period from the survey.

$$X_t = c + \sum_{n=1}^{k} \varphi(n) * X_{t-1} + \sum_{n=1}^{k} \theta(n) * \varepsilon_{t-1} + \varepsilon_t$$

And this equation above, expressed in the form of a time series is called the conditional mean equation. When we combine these two equations, we will have a normally distributed error terms with the mean "0" and non-stable variance.

$$\sigma^2 = \omega + \alpha_t * \varepsilon_{t-1}^2$$

The equation stated above is called as ARCH (1) processes. Shown equation helps to express the error terms of the main equations in a parametric way (Posedel, 2005). With the help of the equation, it can also be seen that how a changing volatility progresses over time in question. ARCH process can be expressed not only with the historical values but also with a longer time period. ARCH (q) q for different periods > 0 condition is to go out in the following manner

$$\sigma^2 = \omega + \sum_{i=1}^{q} . \alpha_i * \varepsilon_{t-i}^2$$

When the constraints that arise (especially when the long term delays are included) in the GARCH model, condition of coefficients' positivity is affected significantly (Bolleslav, 1986). This problem can be solved with the addition the effects of past volatility of the error terms in the ARCH process. The novel process is expressed in the following form and it is called as GARCH (p, q);

$$\sigma^2 = \omega + \sum_{i=1}^{q} .\alpha_i * \varepsilon_{t-i}^2 + \sum_{j=1}^{p} .\beta_j * \sigma_{t-j}^2$$

GARCH (p, q) of the equation parameters are estimated by the maximum likelihood function (Gujarati, 2010). In this equation, p shows moving average; and q shows the number of lags of the error term included in the GARCH process. In this GARCH equation q≥0, p> 0, ω> 0, and βj≥0 αi≥0 conditions should be provided in addition to this α + βj ≤ 1 should be. The total requirement set forth in the parameters of this equation provides stability. Gokce (2001) advocates that, in case of formation of a long-term historical data on the ARCH model, the model would be more efficient and provides more accurate results.

However GARCH includes the past shocks in the volatility estimations, it accepts that the impact of positive and negative shocks would be the same. Unfortunately, this is not always valid. Ozden (2008), Engel (2001) and Posedel (2005), assert that the negative news have more impact than the positive news. In order to solve this problem, EGARCH model was introduced (Nelson, 1991) as follows.

$$Log(\sigma^2) = \omega + \sum_{i=1}^{q} .\alpha_i * Abs(\varepsilon_{t-i}/\sigma_{t-i}) + \sum_{j=1}^{p} .\beta_j * Log(\sigma_{t-j}^2) + \sum_{k=1}^{r} \phi_k(\varepsilon_{t-k}/\sigma_{t-k})$$

Having a coefficient that is equal to zero means that there is an asymmetric effect of the news. And having a coefficient that is less than zero indicates that the negative news has more impact than the positive news and therefore there is a leverage effect.

Another model that advocates an asymmetric effect of positive and negative shocks is TGARCH model. In TGARCH model, Dt-i (independent variable) is added as a dummy variable. This dummy error term

In the case, the dummy error term is less than zero this dummy variable is 1, if there is greater than the value zero dummy variable becomes "0". The value which is greater than zero represents the good news and the value which is less than zero represents the bad news (Hepsag, 2013)

$$\sigma^2 = \omega + \sum_{i=1}^{q} .\alpha_i * \varepsilon_{t-i}^2 + \sum_{j=1}^{p} .\beta_j * \sigma_{t-j}^2 + \sum_{i=1}^{q} .\alpha_i * D_{t-i} * \varepsilon_{t-i}^2$$

.

4. Results

In our research, which is formed between the dates 04.01.2011-26.05.2015, the logarithmic change of daily value or daily logarithmic returns of investors are used.

As shown in the histograms kurtosis values are higher than 3. These values are illustrating that the peak points of the graphs are higher than the normal distribution. A distribution of returns exhibiting high kurtosis as the examples we have tends to overestimate the probability of achieving the mean return. And the mean and medians of the distributions are close to „0". This means that the markets are stable and the long term daily returns are close to zero. Except BOVESPA, the skewnesses of the distributions of the daily returns are negative. It is illustrated by a distribution with an asymmetric tail extending toward more negative values.

As shown in the second and third part of the appendix, by using Eviews and Augmented Dickey Fuller the stability of the daily returns in stock exchange markets is tested. According to the test results there is no unit root in the tests. Therefore, tests proved that the series are stable.

In the Part IV time series estimations have been made. The stability of the series made it enable to use ARMA Maximum Likelihood. This test provides predictions about the behaviour of a time series from past values. The test results are illustrating that all the variables in the series are meaningful with an exemption in BIST100 as it can be seen below.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(3)	-0.008404	0.023026	-0.364963	0.7152

Last but not the least, the ARCH LM tests are included in this study. No heteroscedasticity problem has been found in this research. And the TGARCH coefficients are found to be meaningful and loglikehood values are higher than GARCH values.

5. Conclusion

In this research the volatility of the stock market returns of developing and developed countries which are accepted as changing with time not as fixed are modeled by means of ARCH/ GARCH family models. The question which was asked at the beginning whether there is asymmetric volatility effect which states that the bad news have more effect on volatility than good news are tried to be explained with asymmetric GARCH model namely T-GARCH. By comparing the different models using the log-likelihood values, It is well seen (by means of the model parameters coefficients (especially with T-GARCH coefficients) that the asymmetric effect which is also called as leverage is not only valid for developed or non-developed markets, it is valid for both of those markets. So such a strategy to hedge leverage effect in one stock market with another especially developing against developed would not be a good way of acting.

Moreover any investor who is interested in the market indices must definitely be careful about the position taking by considering the leverage effect (good against the bad news). The time interval fort his research is accepted as the post crisis period starting with the 2011. One might reach the conclusion that, following such big crises all the investors have become more sensitive to the bad news in developed countries. Such sensitivity has been valid for developing countries for a long time because of the almost periodical financial crises like in Turkey and in Brazil. As a result, it can be stated that the markets (free from either developed or developing) are acting similarly against consideration of good and bad news. Such a research could give a light to the future analysis which would like to understand the developing and developed market behaviours as well as hedging strategies against the asymmetric effects on market indices.

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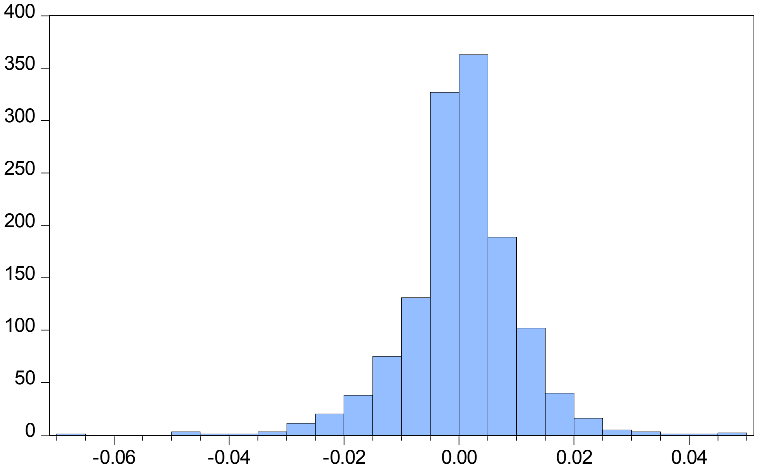
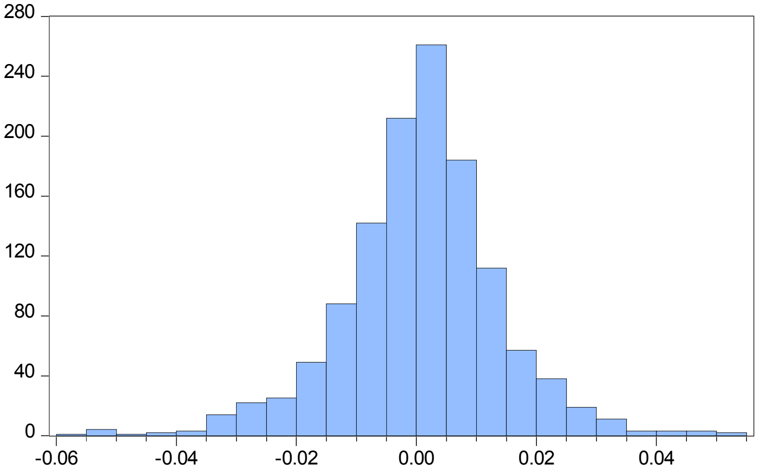
APPENDIX
PART I
Return Histograms

S&P



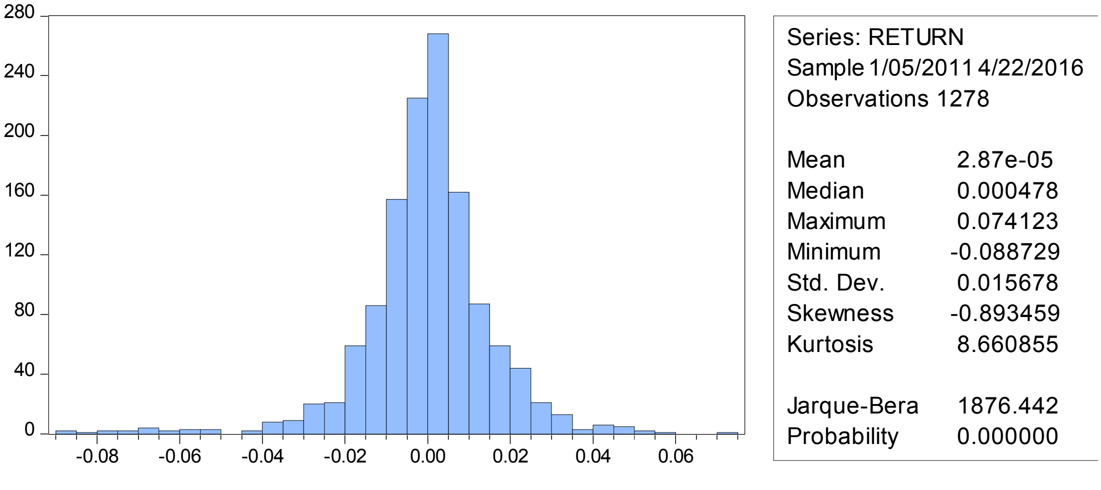
Series: RETURN	
Sample 1/03/2011 4/20/2016	
Observations 1333	
Mean	0.000385
Median	0.000549
Maximum	0.046317
Minimum	-0.068958
Std. Dev.	0.009822
Skewness	-0.480720
Kurtosis	7.499594
Jarque-Bera	1175.857
Probability	0.000000

DAX

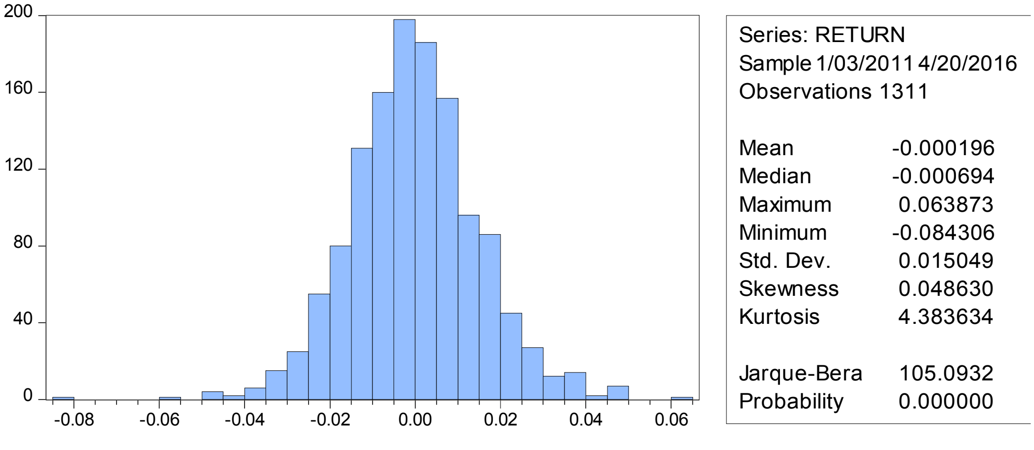


Series: RETURN	
Sample 1/03/2011 4/22/2016	
Observations 1256	
Mean	0.000690
Median	0.001062
Maximum	0.052104
Minimum	-0.059947
Std. Dev.	0.013242
Skewness	-0.198668
Kurtosis	5.050230
Jarque-Bera	228.2423
Probability	0.000000

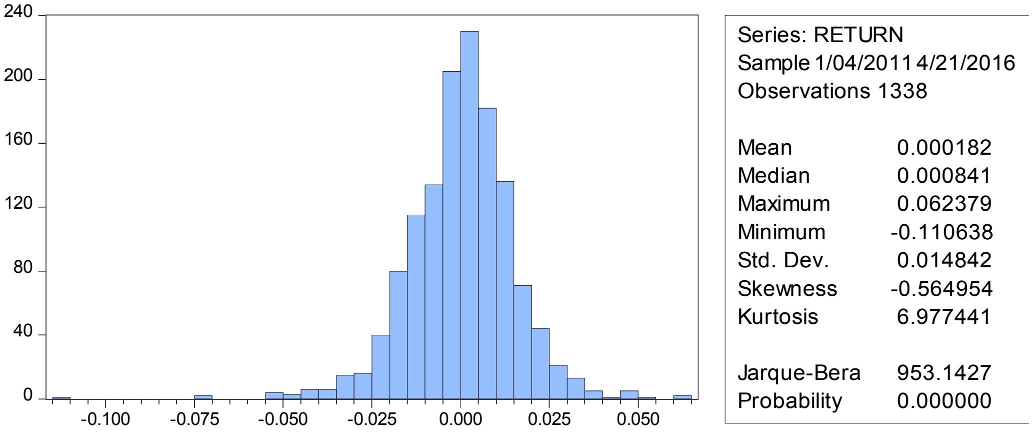
China SHANGHAI STOCK EXCHANGE



BOVESPA



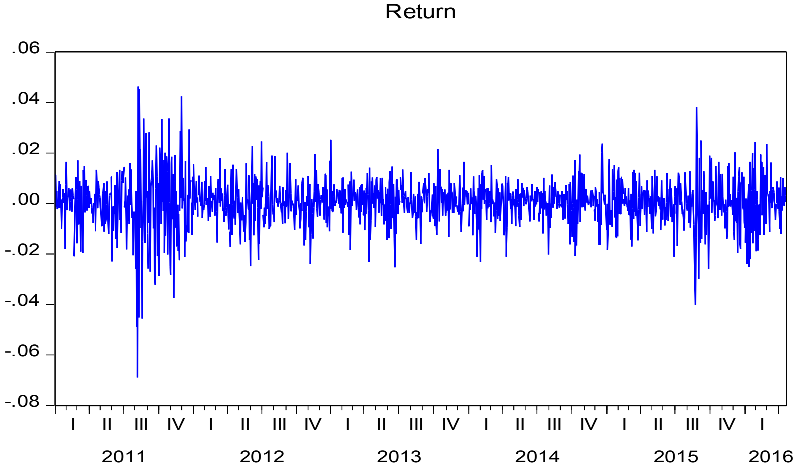
BIST100



PART II

Return Time Series

S&P



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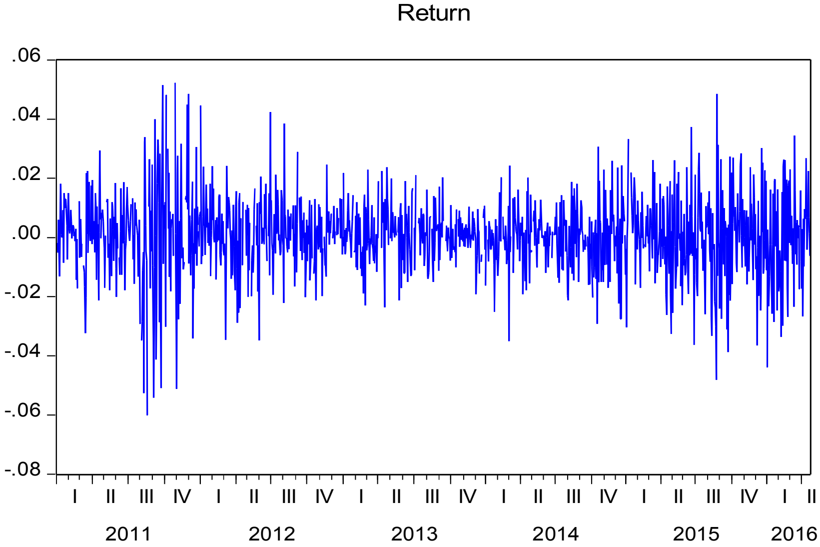
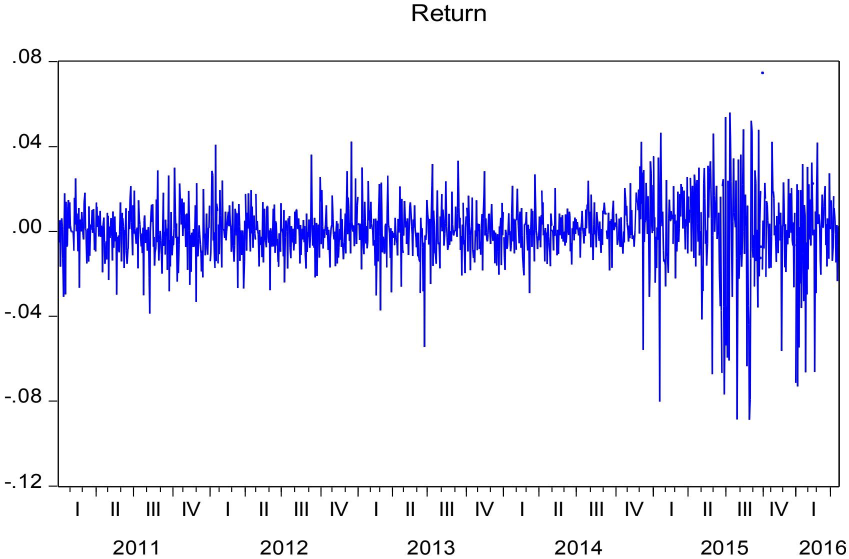
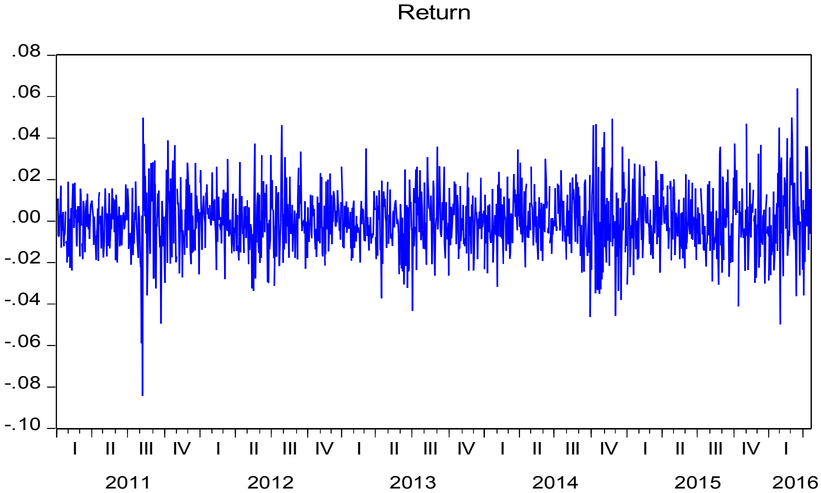


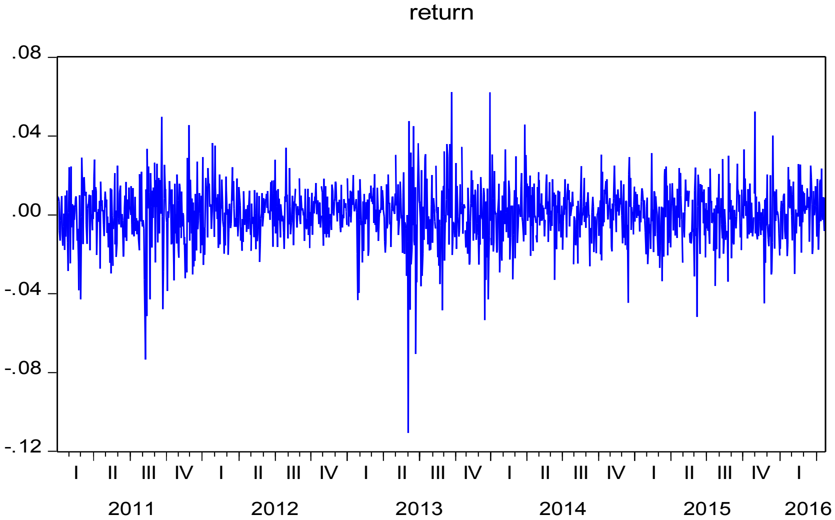
SHANGHAI



BOVESPA



BIST100


return
.08
.04
.00
-.04
-.08
-.12
I
II
III
IV
2011
2012
2013
2014
2015
2016

PART III

ADF TESTS RESULTS

S&P

Null Hypothesis: RETURN has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=22)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-38.28079	0.0000
Test critical values:	1% level	-3.435049	
	5% level	-2.863502	
	10% level	-2.567864	

DAX

Null Hypothesis: RETURN has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=22)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-34.01533	0.0000
Test critical values:	1% level	-3.435527	
	5% level	-2.863714	
	10% level	-2.567978	

*MacKinnon (1996) one-sided p-values.

SHANGHAI

Null Hypothesis: RETURN has a unit root

Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=22)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-33.95659	0.0000
Test critical values:	1% level	-3.435259	
	5% level	-2.863595	
	10% level	-2.567914	

BOVESPA

Null Hypothesis: RETURN has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=22)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-36.01489	0.0000
Test critical values:	1% level	-3.435131	
	5% level	-2.863539	
	10% level	-2.567884	

*MacKinnon (1996) one-sided p-values.

BIST100

Null Hypothesis: RETURN has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=22)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-37.69869	0.0000
Test critical values:	1% level	-3.435030	
	5% level	-2.863494	
	10% level	-2.567860	

PART IV

TIME SERIES ESTIMATIONS

S&P

Dependent Variable: RETURN
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 04/22/16 Time: 18:48
Sample: 1/03/2011 4/20/2016
Included observations: 1333
Convergence achieved after 113 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-1.854882	0.042404	-43.74287	0.0000
MA(1)	0.881318	0.037220	23.67838	0.0000
SIGMASQ	9.53E-05	2.39E-06	39.88419	0.0000

R-squared	0.011575	Mean dependent var	0.000385
Adjusted R-squared	0.008597	S.D. dependent var	0.009822
S.E. of regression	0.009780	Akaike info criterion	-6.413146
Sum squared resid	0.127021	Schwarz criterion	-6.393659
Log likelihood	4279.362	Hannan-Quinn criter.	-6.405844
Durbin-Watson stat	2.009297		

Inverted AR Roots	-.93-.20i	-.93+.2

DAX

Dependent Variable: RETURN
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 04/23/16 Time: 16:16
Sample: 1/04/2011 4/22/2016
Included observations: 1256
Convergence achieved after 47 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000690	0.000378	1.825423	0.0682
AR(1)	-0.958103	0.036688	-26.11501	0.0000
MA(1)	0.972037	0.030265	32.11716	0.0000
SIGMASQ	0.000175	4.93E-06	35.47925	0.0000

R-squared	0.002548	Mean dependent var	0.000690
Adjusted R-squared	0.000158	S.D. dependent var	0.013242
S.E. of regression	0.013241	Akaike info criterion	-5.807552
Sum squared resid	0.219507	Schwarz criterion	-5.791197
Log likelihood	3651.143	Hannan-Quinn criter.	-5.801405
F-statistic	1.066215	Durbin-Watson stat	1.974941
Prob(F-statistic)	0.362405		

Inverted AR Roots	-.96
Inverted MA Roots	-.97

CIN SHANGAI
Dependent Variable: RETURN
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 04/24/16 Time: 14:54
Sample: 1/05/2011 4/22/2016
Included observations: 1278
Convergence achieved after 44 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.205769	0.030679	6.707180	0.0000
AR(2)	-0.960523	0.014945	-64.27160	0.0000
AR(3)	0.076925	0.021354	3.602398	0.0003
MA(1)	-0.153253	0.024805	-6.178414	0.0000
MA(2)	0.910169	0.022470	40.50663	0.0000
SIGMASQ	0.000239	5.40E-06	44.17127	0.0000

R-squared	0.028180	Mean dependent var	2.87E-05
Adjusted R-squared	0.024360	S.D. dependent var	0.015678
S.E. of regression	0.015486	Akaike info criterion	-5.492857
Sum squared resid	0.305045	Schwarz criterion	-5.468664
Log likelihood	3515.935	Hannan-Quinn criter.	-5.483772
Durbin-Watson stat	2.002486		

Inverted AR Roots	.08	.06+.97i	.06-.97i
Inverted MA Roots	.08-.95i	.08+.95i	

BOVESPA

Dependent Variable: RETURN
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 04/23/16 Time: 15:01
Sample: 1/03/2011 4/20/2016
Included observations: 1311
Failure to improve objective (non-zero gradients) after 29 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.323747	0.004560	71.00073	0.0000
AR(2)	-0.991383	0.005103	-194.2844	0.0000
MA(1)	-0.315426	0.095776	-3.293367	0.0010
MA(2)	1.000000	0.606270	1.649429	0.0993
SIGMASQ	0.000224	6.73E-05	3.328954	0.0009

R-squared	0.009916	Mean dependent var	-0.000196
Adjusted R-squared	0.006883	S.D. dependent var	0.015049
S.E. of regression	0.014997	Akaike info criterion	-5.555021
Sum squared resid	0.293741	Schwarz criterion	-5.535271
Log likelihood	3646.316	Hannan-Quinn criter.	-5.547614
Durbin-Watson stat	2.010462		

Inverted AR Roots	.16-.98i	.16+.98i
Inverted MA Roots	.16+.99i	.16-.99i

BIST 100

Dependent Variable: RETURN
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 04/22/16 Time: 14:07
Sample: 1/04/2011 4/21/2016
Included observations: 1338
Convergence achieved after 46 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-1.677286	0.033316	-50.34497	0.0000
AR(2)	-0.990202	0.047153	-20.99955	0.0000
AR(3)	***-0.008404***	***0.023026***	***-0.364963***	***0.7152***
MA(1)	1.653466	0.025841	63.98492	0.0000
MA(2)	0.955823	0.026325	36.30789	0.0000
SIGMASQ	0.000218	5.11E-06	42.67934	0.0000

R-squared	0.009144	Mean dependent var	0.000182
Adjusted R-squared	0.005424	S.D. dependent var	0.014842
S.E. of regression	0.014802	Akaike info criterion	-5.583556
Sum squared resid	0.291821	Schwarz criterion	-5.560242
Log likelihood	3741.399	Hannan-Quinn criter.	-5.574821
Durbin-Watson stat	1.998907		

PART V

ARCH-LM Test

S&P

Heteroskedasticity Test: ARCH

F-statistic	3.739468	Prob. F(1,1329)	0.0534
Obs*R-squared	3.734588	Prob. Chi-Square(1)	0.0534

DAX

Heteroskedasticity Test: ARCH

F-statistic	11.437519	Prob. F(1,1347)	0.0084
Obs*R-squared	11.438026	Prob. Chi-Square(1)	0.0084

BOVESPA

Heteroskedasticity Test: ARCH

F-statistic	5.051817	Prob. F(1,1306)	0.0204
Obs*R-squared	5.051895	Prob. Chi-Square(1)	0.0204

CIN SHANGAI

Heteroskedasticity Test: ARCH

F-statistic	8.326174	Prob. F(1,1306)	0.0092
Obs*R-squared	8.207694	Prob. Chi-Square(1)	0.0092

BIST100

Heteroskedasticity Test: ARCH

F-statistic	27.143217	Prob. F(1,1329)	0.0004
Obs*R-squared	27.143321	Prob. Chi-Square(1)	0.0004

PART VI

GARCH and TGARCH results

		BIST100		DAX		BOVESPA		SP			SAX			BUX	
	Variable	Value	Prob	Value	Prob	Value	Prob			Variable			Variable		
	C			0.0682	0.000690										
	AR(1)	-1,677,286	0.0000	0.0000	-0.958103	0.323747	0.0000	-1,854,882	0.0000		0.205769	0.0000		1,110,736	0.0000
	AR(2)	-0.990202	0.0000			-0.991383	0.0000				-0.960523	0.0000		-0.567564	0.0015
	AR(3)	-0.008404	0.7152								0.076925	0.0003		-0.044506	0.1338
	AR(4)														
	MA(1)	1,653,466	0.0000	0.0000	0.972037	-0.315426	0.0010	0.881318	0.0000		-0.153253	0.0000		0.1131041	0.0014
	MA(2)	0.955823	0.0000			1000000	0.0993				0.910169	0.0000		0.584411	0.0000
Main Equation	MA(3)														
	Variable	Value	Prob	Value	Prob	Value	Prob			Variable			Variable		
	C			0.000690	0.0682					C			C		
	AR(1)	-1,649,948	0.0000	-0.926062	0.0000	1,426,546	0.0344	-0.899679	0.000	AR(1)	-0.652572	0.0422	AR(1)	-0.275529	0.0608
	AR(2)	-0.948954	0.0000			-0.554416	0.3920			AR(2)	0.266142	0.3866	AR(2)	0.054621	0.8517
	AR(3)	0.018452	0.05684							AR(3)	-0.066642	0.0001	AR(3)	-0.082085	0.0011
	AR(4)	-	-							AR(4)			AR(4)		
	MA(1)	1,651,430	0.0000	0.948640	0.0000	-1,412,236	0.0402	0.853014	0.0000	MA(1)	0.713445	0.0245	MA(1)		
	MA(2)	0.960503	0.0000			0.533773	0.4205			MA(2)	-0.284654	0.0367	MA(2)	0.326764	0.2773
	MA(3)	-	-							MA(3)			MA(3)	-0.067714	0.8213
	C	0.000200	0.0000	1018701	0.0000	0.000214	0.0000	7.62E-05	0.0000	C	0.000177	0.0000	C	0.000132	0.0000
	RESID(-1)^2	0.081069	0.0000	-0.018019	0.0000	0.051348	0.0313	0.197153	0.0000	RESID(-1)^2	0.294199	0.0000	RESID(-1)^2	0.188177	0.0000
ARCH	Log Likelihod	3740.81		3971.14		3442		4311		Log Likelihod	3550		Log Likelihod	3890	
	C			0.0007140	0.0543					C			C		
	AR(1)	0.401542	0.0000	-0.988663	0.0000	0.310493	0.0000	-0.320793	0.5014	AR(1)	-0.106398	0.7645	AR(1)	-0.466441	0.3294
	AR(2)	-0.978698	0.0000			-0.947231	0.0000			AR(2)	0.857399	0.0104	AR(2)	-0.121309	0.7843
	AR(3)	0.000844	0.9792							AR(3)	-0.009616	0.7639	AR(3)	-0.045536	0.1452
	AR(4)	-								AR(4)			AR(4)		
	MA(1)	-0.405611	0.0000	0.997986	0.0000	-0.299781	0.0000	0.308089	0.5213	MA(1)	0.136680	0.7002	MA(1)	0.483584	0.3141
	MA(2)	0.996258	0.0000			0.959851	0.0000			MA(2)	-0.861078	0.0151	MA(2)	0.117982	0.7944
	MA(3)	-	-							MA(3)			MA(3)		
	C	1.14E-05	0.0000	1.74E-06	0.0053	5.07E-06	0.0024	4.63E-06	0.0000	C	1.59E-06	0.0003	C	5.99E-06	0.0001
	RESID(-1)^2	0.079418	0.0000	0.056661	0.0000	0.058100	0.0000	0.149229	0.0000	RESID(-1)^2	0.048950	0.0000	RESID(-1)^2	0.067676	0.0000
	GARCH(-1)	0.869727	0.0001	0.933783	0.0000	0.920510	0.0000	0.799583	0.0000	GARCH(-1)	0.944193	0.0000	GARCH(-1)	0.894182	0.0000
GARCH(1,1)	Log Likelihod	3792.14		4005.17		3646		4451		Log Likelihod	3614		Log Likelihod	3941	
	C			0.000420	0.0782					C			C		
	AR(1)	-1,559,842	0.076766	0.962930	0.0000	0.841797	0.0000	-0.416052	0.2690	AR(1)	-0.009127	0.9837	AR(1)	0.040159	0.0432
	AR(2)	-0.809601	0.087815			0.144205	0.1811			AR(2)	0.798638	0.0414	AR(2)	-0.774092	0.0000
	AR(3)	0.047897	0.031564			-0.831720				AR(3)	-0.028741	0.4324	AR(3)	-0.001411	0.9614
	AR(4)	-	-			-0.167859				AR(4)			AR(4)		
	MA(1)	1,567,454	0.072311	-0.937018	0.0000	-0.831720	0.0000	0.427590	0.2537	MA(1)	0.069324	0.8766	MA(1)	-0.031304	0.8270
	MA(2)	0.840993	0.069427			-0.167859	0.1375			MA(2)	-0.808817	0.0568	MA(2)	0.775840	0.0000
	MA(3)	-	-							MA(3)	2.40E-06	0.0012	MA(3)		
	C	1.46E-05	0.0000			4.41E-06	0.0015	4.06E-06	0.0000	C	2.40E-06	0.0012	C	2.18E-06	0.0503
	RESID(-1)^2	0.022054	0.1963	1.01E-06	0.0008	0.049911	0.0140	-0.063578	0.0000	RESID(-1)^2	0.060390	0.0000	RESID(-1)^2	0.034405	0.1106
	RESID(-1)^2*(RESID(-1)<0)	0.198986	0.0000	-0.029138	0.0001	0.096543	0.0000	0.346333	0.0000	RESID(-1)^2*(RESID(-1)<0)	0.062939	0.0074	RESID(-1)^2*(RESID(-1)<0)	0.205854	0.0000
	GARCH(-1)	0.235107	0.0057	0.114243	0.0000	0.044315	0.0320	0.851961	0.0000	RESID(-2)^2	0.130494	0.0000	RESID(-2)^2	0.049364	0.0423
	GARCH(-2)	0.616782	0.0000	0.967425	0.0000	0.936783	0.0000			RESID(-2)^2*(RESID(-2)<0)	0.060318	0.0137	RESID(-2)^2*(RESID(-2)<0)	0.182510	0.0000
TGARCH (1,1,1)	Log Likelihod	3809.71		4084.17		3711		4504		GARCH(-1)	0.785937	0.0001	GARCH(-1)	0.1585398	0.0000
										GARCH(-2)	0.132577	0.0000	GARCH(-2)	0.625203	0.0000
									TGARCH (1,1,2)	Log Likelihod	3700		Log Likelihod	3950	