Pakistan Economic and Social Review
Volume 57, No. 2 (Winter 2019), pp. 163-197

EVIDENCE OF VOLATILITY CLUSTERING AND ASYMMETRIC BEHAVIOR OF RETURNS IN ASIAN EMERGING STOCK MARKETS

SYED M. WAQAR AZEEM NAQVI, KANWAL IQBAL KHAN,
MUHAMMAD MUDASSAR GHAFOOR AND SYED KUMAIL ABBAS RIZVI*

Abstract. In financial time series, the volatility clustering and asymmetry behavior is a vital fact. In this very research, we focus on the important aspects of the existence of volatility clustering and asymmetry by employing the GARCH models which include both symmetric models and asymmetric models on eight Asian emerging financial markets. This research has used log-returns of selected financial markets monthly indexes from 2009 to 2018. This study finds the existence of financial asymmetric behavior and clustering volatility in all sample financial stock markets. The study confirms that asymmetric behavior is high if volatility clustering of returns exists. On the other hand, good news impacts less compared to unfavorable news on t+1 day volatility and vice versa. This study assesses the prognostic ability of asymmetric and symmetric GARCH models and comes out that the asymmetric GARCH models are performed well in capturing the volatility clustering and asymmetric

*The authors are respectively Financial Advisor at Canadian Imperial Bank of Commerce (CIBC) Toronto – Canada, Assistant Professor at Institute of Business & Management, University of Engineering and Technology, Lahore, Director at University of the Punjab, Jhelum Campus and Associate Professor at Department of Finance, Lahore School of Economics, Lahore – Pakistan. Corresponding author's e-mail: drkanwaliqbalkhan@gmail.com

behavior than symmetric GARCH on emerging Asian financial markets.

Keywords: Asymmetric, Volatility clusters, News impact, symmetric GARCH, Asymmetric G-GARCH and E-GARCH, Investment Decision, Portfolio risk and return

JEL Classification: G10, G11, G15, G52

I. INTRODUCTION

Due to continuous fluctuation in stock market indices the nature of financial markets is stochastic (Moliner, & Epifanio, 2019). Investors always tend to invest in those markets where they can meet their risk-return expectations especially due to the presence of uncertainty and volatile movement of stock indices (Cao, Zhang, & Li, 2017). This bullish- bearish (up-down) movements in daily stocks prices are identified as returns' volatility. These up and down movements are considered as normal unless these movements' turn into infrequent like very low or high (Khan, Khan, Mahmood, & Sheeraz, 2019). These unusual movements not only distort the investor confidence but also investment flow and investment planning. Higher volatility in stock indexes leads to increase the uncertainty about expected returns and increase risk (Ning Xu, & Wirjanto, 2008). Prediction about risk-return in instable financial markets is very hard for investor and makes him shaky in making investment decision in that particular market. This uncertainty in markets forbids rational investors to invest in particular volatile market.

Companies face difficulty in raising their capital from financial markets due to volatile situation. It also results in loss of existing and potential investors which in return causes more severe volatile situations for the companies (Bouchaud, Gefen, Potters, & Wyart, 2004). Sometime this uncertainty leads towards financial distress as observed in 2008 and 2011 (Hashmi & Tay 2007). Therefore, it becomes necessary to avoid such situations by accurately assessing the risk measures. As investors are always interested in high returns and low risk which can be difficult to obtain as in financial studies high returns are associated with high risk

(Coskun & Ertugrul. 2016). One can minimize risk but cannot avoid it due to high fluctuations in daily stock prices or even in forex rates which causes sometimes high returns or can often results huge losses (Hoy, 1988; Hull, 2012).

The stock returns in emerging markets are more volatile. Investors want to maximize their portfolio returns however, there is a commonly known fact exists that the relationship between stock returns and volatility is inverse (Coskun & Ertugrul. 2016; Pagan & Schwert 1990). This issue is also recognized as asymmetry. Black (1976) concluded that decrease in stock returns enhances the leverage and in return this leverage effect increases the volatility clustering and asymmetry risk. We can also say that if there is a combination exist between volatility clustering and asymmetry then it is known as leverage effect which can affect both risk and return of stocks (Patton & Sheppard, 2015; Campbell & Hentschel, 1992; Naqvi et al., 2016). The emerging markets then follow the trend of high risk and high return and increasing risk level results the demand of high expected return on investment. Therefore, the relationship between leverage and volatility is casual and different. Previously, the common direction of relationship flow is from return to conditional volatility while now the relationship flow direction reverses from volatility to returns. So, the importance to measure risk before making an investment decision for a specific market and that ultimately helps in good portfolio construction as well as for asset pricing.

For long time, the assumption of normal distribution and stock market returns' performance distribution are aligned. This discrepancy comes out if stock market returns are measured with consideration of asymmetry (skewness) and volatility clustering (kurtosis). The emphasis to incorporate the third and fourth measure of risk was pointed out by the behavior of stock risk-return the assumption of normal distribution and standard deviation (Harvey & Siddique, 2000; Naqvi et al., 2017). The tradition of GARCH models is to integrate the clustering volatility and that is defined as a big shocks followed by big or small shocks regardless of their volatility due to directional effects (positive/negative) (Timmer, 2018). The biggest limitation of traditional symmetric GARCH models was that it does not integrate the effects of favorable or unfavorable news on volatility risk (Horvath & Johnston, 2010). The introduction of

Exp-GARCH and GJR-GARCH has ended this limitation of traditional models. According to exponential-GARCH, Nelson (1991) presented this model, the measurement of asymmetric shocks is vital (favorable or unfavorable). Another asymmetric model GJR-GARCH is introduced by Glosten, Jagannathan, & Runkle, (1993) which is the extension of GARCH (p, q) also known as TGARCH, this is also used to measure the volatility clustering and asymmetric risk. Therefore, it is necessary for the investors to avoid risk in order to maximize the returns and obtain optimal portfolio. This can only be possible if advanced and reliable tools and techniques are applied for measuring the risk as the stock market returns in emerging Asian markets which are considered more volatile. That is why, Khan et al., (2019) suggested that in emerging economies investors can avoid risk and make optimal investment decision only through accurate measurement of volatility.

This study focuses on the consideration of third and fourth moment of risk which is ignored while making investment decision. The traditional mean- variance criteria based on modern portfolio theory still is the primary criteria for many investors while making investment decisions ignoring the factual presence of skewness and kurtosis. However, grim ambiguity exists on the mean-variance decisions because such decisions takes normality assumption which could be a dream in financial time series. By taking this argument, this study tries to test the presence of third and fourth moment of risk and argue that in presence of additional risk decisions should be taken accordingly. This study aims to bring forward the presence of risk proxies that include third and fourth movement of risk refer as asymmetric behavior and volatility clustering respectively for Asian emerging financial markets using symmetric and asymmetric GARCH models. In this way, it provides more predictable and reliable measures of risk and return to investors and also contributes in the investment finance literature in the following ways: Firstly, it gives models to measure asymmetry (third movement of risk) and volatility clustering (fourth movement of risk) for Asian financial markets and that adds comprehensively in finance literature as well. Secondly, it contributes by concluding that asymmetric GARCH models are leading the way by incorporating the third and fourth movement of risk compare to symmetric GARCH for Asian emerging stock markets, chose for this study which can help in investment decision making by considering the presence of these additional risks. Thirdly, it formulates a suggestion for individual, retail, and institutional investors in policy formulation which could be more realistic provided the presence of these risk and expected return would be accurate. Eventually, the risk reporting mechanism especially in the existence of asymmetric risk and volatility clustering would be a decisive factor in investment decision making and investment flow for a particular market.

II. REVIEW OF LITERATURE

Time series data normally deals with the three most important and widely discussed phenomena of investment finance i.e., volatility clustering, lepto-kurtosis and leverage effect (Akashi, Bai, & Taqqu, 2018). Volatility clustering depicted the periods of fluctuations where large or small variations in data are followed by the periods of large or small fluctuations in stock market (Madan & Seneta, 1990). Therefore, Timmer, (2018) confirmed the effect of past events on the next day stock volatility. Kurtosis risk is also existed in the financial time series data due to volatility clustering. In this situation, investors neither optimized their portfolios nor appraised stock market prices without recognizing the volatility clustering (Khan *et al*., 2019).

In financial leverage presence, Christie (1982) and Glosten et al., (1993) had studied the level of relationship among returns and volatility. They described that if financial leverage is present then not only correlation between risk and past returns is negative but there is also negative relationship between these two. High risk high return principle comes into effect if volatility is high in a market then investor expects high return. The scholars like Hoy, (1988) and Lau and Lau. (2005) believed that favorable or unfavorable news has a symmetric effect risk volatility. But volatility clustering can be a handy instrument to capture the dynamics of asset’s risk deviations (Hoy, 1988). Therefore, it is essential to determine the presence of volatility clustering in financial time series. As it further leads to access the intensity of kurtosis risk due to its presence because high fluctuations in returns increases the kurtosis risk while low fluctuations cause reduction in risk levels (Coskun & Ertugrul. 2016; Ning *et al.*, 2008).

Bouchaud *et al*., (2004) studied volatility clustering by employing ARCH family models based on financial time series data in order to confirm the ARCH effect because of it. Their findings confirmed the presence of direct positive relation between volatility clustering and kurtosis. They further elaborated that the ARCH effect is present only in the hypothetical market with kurtosis (lepto-kurtosis) and volatility clustering (Horvath & Leipus, 2009). Cao et al., (2017) also confirmed this relationship after comparing the measuring abilities of volatility models by using asymmetry methods. Their study found that volatility clustering increases the kurtosis risk, asymmetry and skewness risk. Tseng and Li (2012) confirmed these findings by added that negative clustering left long lasting influence in the stock market than positive clustering that further leads towards skewed distribution of returns rather than gaussian distribution.

To find out the volatility pattern whether this volatility clustering flows systematically from asset returns GARCH models are very handy whereas Exp-GARCH and GJR-GARCH are in a better position to explain the asymmetric effect of volatility clustering in financial time series (Lau & Lau. 2005). Prior literature showed that asymmetry risk arises due to high volatility clustering of returns (Alberg, Shalit, & Yosef, 2008) which can be measured through skewness. Skewness is the third moment of risk (Campbell and Hentschel, 1992) and is a widely used financial measure in the time series studies (Bouchaud *et al*., 2004; Patton & Sheppard, 2015). But still researchers like Khan et al., (2019) believed on the need of new econometric techniques and better proxies of volatility clustering to accurately evaluate the asymmetric behavior of stock returns. As the financial returns are quite unpredictable in nature and volatility modelling with simple methods like average, standard deviation, coefficient of variation etc., may not provide accurate results (Hoy, 1988). Therefore, it becomes necessary to select an appropriate model of risk measurement in order to obtain reliable results (Alberg *et al.*, 2008).

Recently, ARCH family models are applied to address this issue (Moliner, & Epifanio, 2019). These models are considered better for measuring the conditional volatility in financial market data and provide conditional variance based on reliable past squared residuals for volatility clustering. Previously many researchers used ARCH models for estimating the risk variances. Engle & Ng, (1993) estimated the fluctuation in inflation at UK, Bollerslev (1986) used GARCH models for measuring the risk variations. Nelson (1991) proposed Exponential-GARCH model for determining volatility clustering and asymmetry risk in time series data which is helpful in identifying skewness of positive or negative shocks.

Baillie (1996) introduced GARCH model for measuring volatility risk. Glosten et al., (1993) and Patton and Sheppard, (2015) extended GARCH (p, q) to assess the additional asymmetric risk. Rizvi, Naqvi, Bordes, & Mirza, (2014) used GJR-GARCH model to analyze the changing patterns of volatility and asymmetry risks. Financial market data is generally volatile and is subjected to intense tailed that typically do not allow asymmetric returns (positive/negative) or even skewness modelling. In this situation GARCH and ARCH family models can perform better and provide better results (Hansen & Lunde, 2005). In order to make more precise estimation of asymmetric behavior and volatility clustering, now finance scholars prefer to use ARCH family models that includes GARCH, M-ARCH, E-GARCH, GJR-GARCH (T-ARCH) and P-ARCH for estimating volatility clustering and asymmetry risks (Bekaert & Wu, 2000).

Currently, many researchers tried to identify the asymmetry risk factors involved in financial market data (Akashi et al., 2018; Kim and White, 2004; Rizvi et al., 2014). They concluded that investors can employ skewness factors along with GARCH models for accurate calculation and forecasting of risk. However, Harvey and Siddique (1999) believed that investors first evaluate conditional T-distribution and then apply combination of T-distribution along with outline factors in the second or third step. Lanne & Saikkonen (2007) applied M-GARCH method of measurement of skewness risk by combining Z-distribution and consider it better in evaluating volatility clustering. Lau and Lau, (2005) has also implemented GARCH models in which conditional variance and asymmetry (skewness) increase the fit of spill over models. Kim and White, (2004) and Chen, Hong, and Stein, (2001) found that the stocks earning larger abnormal returns in the past are more negatively skewed. A study by Hansen and Lunde (2005) confirmed that GARCH family models are the best to measure the asymmetry risks and volatility clustering.

At this time, skewness (third) and kurtosis (fourth) have caught attention of being a vital component which should not be overlooked while making investment decision. The importance of taking the consideration of third and fourth moment of risk is stressed (Beardsley, Field, and Xiao, 2012; Guidolin and Timmermann, 2008; Li, Qin, and Kar, 2010; Liu, Liu, and Wang, 2013; Naqvi et al., 2017 and Wilcox and Fabozzi, 2009). Due to the presence of volatility clustering which makes financial times series non-convex and less smooth especially in emerging markets the ignorance could be costly for investors and policy makers. The efficient market hypothesis (EMH) states that the news impact reflects in the stock prices but the news impacts differently in emerging markets which leads to asymmetric behavior (Liu et al., 2013; Naqvi et al., 2017). In this study we argue that the presence of asymmetric behavior and volatility clustering in emerging markets should not be overlooked. This study contributes to finance literature that volatility clustering exists in the Asian emerging markets and should be a vital consideration for the investors before making investment decision in these markets and only mean- variance based decision can penalize investors.

III. RESEARCH METHODOLOGY

In this study, we have chosen the eight Asian emerging markets and our selection criteria on these emerging markets is based on the Standard and Poor’s emerging market index. We choose index return of following financial markets: SSE Composite (China), Hang Seng (Hong Kong), CNX500 (India), FTSE Bursa (Malaysia), KSE100- PSX (Pakistan), Straits Times-STI (Singapore), SE KOSPI 200 (South Korea) and SE Weighed TAIEX (Taiwan). This study used the monthly data of above listed indices of ten year from 2009 to 2018. Log returns are calculated for each financial market in our sample indices by using following method:

$$R_t = \log \frac{P_t}{P_{t-1}}$$

While R_t are monthly returns at time t and P_t price. In order to check the data stationarity, this study has run Unit Root test. We have also checked the ARCH effect on selected data prior to the application of GARCH models by running ARCH test. Our test results negate the presence of Unit Root but affirm the ARCH affect and support the use of ARCH family models (see appendix).

MEAN EQUATION, GARCH MODELS CONSTRUCTION AND APPLICATION:

Bollerslev (1986) was the first who came up with more sophisticated method to measuring of volatility clustering called GARCH which became the significant way for the measurement of volatility clustering. His work was the extension of his predecessor Engle & Ng, (1993) the one who introduced the method to measure the conditional variance named Autoregressive Conditional Heteroscedastic (ARCH). The lagged return function autoregressive AR- (1) process is used in this study. One of the reasons to use the lagged function is to see the level of efficiency in the selected markets in case of new impact (Horvath & Johnston, 2010). Many studies confirm the importance of lagged function AR-(1) term φ1Rt-1 (Cao *et al*., 2017; Hoy, 1988; Rizvi et al., 2014).

$$R_t = \varphi_0 + \sum_{i=1}^{k} \varphi_1 R_{t-1} + E_t \quad --------$$

Whereas, $E_t = \sum_{i=1}^{A} A_i E_{t-i} + \sum_{i=1}^{B} B_i E_{t-i} + \epsilon_t$

VARIANCE EQUATION

In order to measure the volatility of returns we have used GARCH in this study.

$$\sigma_t = \alpha + \beta\epsilon_{t-1} + \gamma\sigma_{t-1} \quad ------(a)$$

Equation-a is the measure of volatility in form of square root. However, we need the equation to measure the mean square deviations so we drive equation-b by taking square of equation-a

$$\sigma_t^2 = \alpha + \beta\epsilon_{t-1}^2 + \gamma\sigma_{t-1}^2 \quad ------(b)$$

While variance σ_t^2 is denoted as G_t and that is the residual variance resulting from mean equation or t-day risk of sample financial markets. The equation for conditional variance follows as:

$$G_t = \alpha + \sum_{i=1}^{q} \beta_i \; \epsilon_{t-i}^2 \; + \; \sum_{j=1}^{p} \gamma_j \, G_{t-j} \quad -------- \qquad \mathbf{1}$$

$$where \;\; \alpha > 0, \beta_i \geq 0 \;\&\; i = 1,2,3,4,5,6,7,8 \ldots \ldots q$$

$$\gamma_j \geq 0 \;\&\;\; j = 1,2,3,4,5,6,7,8, \ldots \ldots p$$

G_t = t-day residuals variance which comes from equation - one. Whereas ϵ_{t-j}^2= lagged squared residuals from equation – one which is an ARCH term in the model to check lagged volatility information of stock returns.

CONSTRAINT OF GARCH MODEL

In order to capture large symmetrical shocks and volatility clustering GARCH is better measure of conditional risk σ_t^2 compare to ARCH (Bollerslev, 1986). However, the drawback with GARCH model is that it assumes that volatility is symmetric regardless of shock direction either positive or negative. It is better to use ARCH family models for risk measurement in case returns are distributed symmetrically but in real financial data this could be a dream (Hoy, 1988). By looking at semi-variance of returns, various studies say, it is more credible measure of risk due to upside volatility generally liked by individual or institutional investors (Cao et al., 2017). On the other hand, investors do not like downward volatility as well as asymmetric returns' distribution (Alberg et al., 2008). In this study, we capture the asymmetric volatility behavior by using diverse models of asymmetric risk measurement like asymmetrical GARCH models (Christie, 1982; Patton & Sheppard, 2015) (GJR- GARCH and E-GARCH) (Akashi et al., 2018; Khan et al., 2019; Lau & Lau. 2005). To model the asymmetric behavior the derivation is as follow:

$$\sigma_t = \alpha + \; \beta\sigma_{t-1} \left| \epsilon_t \right| + \gamma\sigma_{t-1} \quad ------(c)$$

$$\sigma_t = \alpha + \; \beta\sigma_{t-1} \left| \epsilon_t - x \right| + \gamma\sigma_{t-1} \; ----(d)$$

$$\sigma_t = \alpha + \beta\sigma_{t-1}[|\epsilon_t| - y\epsilon_t] + \beta\sigma_{t-1} \quad ----(e)$$

$$\sigma_t = \alpha + \beta\sigma_{t-1}[|\epsilon_t - x| - y(\epsilon_t - x)] + \gamma\sigma_{t-1} ----(f)$$

While, $F(\epsilon_t) = |\epsilon_t - x| - y(\epsilon_t - x)$

EXP-GARCH and GJR-GARCH Models derivation

To measure the conditional variance and asymmetrical risk with signs of distress either positive or negative, exponential GARCH is the better due to ability to capture asymmetric behavior (Nelson, 1991). The positive side of this model is that helps capturing and modelling skewness either positive or negative, which is third measure of risk.

$$X_t = \text{EXP}\left(\frac{G_t}{2}\right)\varepsilon_t, \qquad whereas \qquad G_t^2 = \gamma_0 + \gamma_1 G_{t-1} + l(\varepsilon_{t-1}) - (g)$$

while $\quad l(x) = \omega x + \lambda(|x| - E|x|)$

$$G_t = \alpha + \sum_{i=1}^{q} \alpha_i \left| \frac{\epsilon_{t-i}}{\sqrt{G_{t-i}}} \right| + \sum_{j=1}^{p} \beta_j \log G_{t-1} + \sum_{k=1}^{r} \gamma_k \frac{\epsilon_{t-k}}{\sqrt{G_{t-k}}} \qquad ------(h)$$

Another measure to capture the asymmetric behavior of financial returns is GJR-GARCH which is a stretched version of symmetric GARCH (p, q) but have ability to capture the additional asymmetric risk.

$$G_t = \alpha + \beta_i \epsilon_{t-i}^2 + \gamma_i \epsilon_{t-i}^2 l_{t-i} + \varphi_j G_{t-j} \qquad ----\mathbf{3}$$

IV. RESULTS

GARCH (p, q) results are shown in Table A of the selected Asian emerging financial markets indexes. The results of GARCH (p, q) parameters (α and β) are not only statistically significant at probability of one percent but also positive for all selected Asian emerging financial markets.

Table -A

GARCH (p, q)

Coefficients	SSE composite	Hang Seng Index	CNX500	FTSE Bursa	KSE100	STI Index	SE KOSPI 200	SE Weighed TAIEX
Mean Equation								
ω_0	-0.00294	0.00911	0.0140*	0.0079**	0.0229***	0.0073	0.0067*	0.0077*
ω_1	-0.01603	0.01512	0.0570	0.0092	-0.029	0.0632	-0.0914	0.0522
Variance Equation								
α	0.00029	0.000371*	0.00041	0.00013	0.00047*	0.000197	4.20E-04	0.000126
β	0.1951*	0.2891**	0.1011*	0.154**	0.1930***	0.2197***	0.1783***	0.2411*
γ	0.784***	0.6324***	0.839***	0.753***	0.769***	0.7280***	0.8192***	0.7292***
R-square	-0.0074	-0.0011	0.0054	0.0017	-0.0193	0.0203	-0.0064	0.0119
R-square Adjusted	-0.0160	-0.0096	-0.0030	-0.0069	-0.028	0.01197	-0.01496	0.0035
AIC[1]	-2.165	-2.872	-2.248	-3.792	-2.229	-3.189	-3.498	-3.019
SIC[2]	-2.048	-2.755	-2.131	-3.675	-2.113	-3.073	-3.382	-2.903

*** 1 Percent, ** 5 Percent, * 10 percent

[1] Akaike info criterion
[2] Schwarz criterion

The β parameter in all emerging market indexes are in between from 0.63 to 0.83 as well as positive in all selected financial emerging markets and that indicates the presence of constant volatility clustering. However, by looking at individual market, the volatility clustering is lower in Hang Seng Index (Hong Kong) (0.632) compare to others while it is highest in CNX500 (India) with a β parameter of (0.838) followed by SE KOSPI 200 (South Korea) with 0.819. While rest of the financial markets in the sample are reflecting less volatility clustering compares to other discussed above in long-run which also point out towards market efficiency. By looking at decision parameters (α, β) the summation of those are above 0.90 which is an indication high volatility clustering (large positive and negative returns). The decision rule for a good GARCH (1, 1) is that the α and β parameters summation should be less than 1. The results of this study are less than 1 and falls under the decision rules to conclude the presence of volatility clustering. GARCH (p, q) model works on the assumption of symmetric parameters. So, this study goes further to check the asymmetric behavior and news impact (positive, negative) on financial returns so we use heteroskedastic asymmetric models to check the existence of asymmetry in selected Asian emerging stock markets.

EGARCH results are presented in Table B which show the estimation of the parameters of selected Asian emerging financial markets. As described earlier that the EGARCH measures asymmetric volatility as well as aid in finding out the relation between logarithm conditional variance volatility and lagged returns. To make EGARCH friendly to use compare to other different GARCH models log specification is important. EGARCH includes the lagged time (in this study we used time as month) for negative shocks on conditional volatility log that is $\alpha - \beta$ on the other hand $\alpha + \beta$ is a positive shock or favorable news. Results show that the impact if news is less on volatility during longer period of time and summation of α and β parameters show this. As per γ assumption it should be positive. However, in volatility modeling unfavorable news shock impacts more compare to positive shock on variance which is $\alpha - \beta > \alpha + \beta$. Based on the explained criteria if we look at the result table B except SSE Composite (china) where γ is negative while in all other Asian emerging markets it is positive which

Table -B
EXP-GARCH

Coefficient	SSE composite	Hang Seng Index	CNX500	FTSE Bursa	KSE100	STI Index	SE KOSPI 200	SE Weighed TAIEX
Mean Equation								
ω_0	0.0048**	0.0081	0.0125**	0.0067*	0.022***	0.0091**	0.0019**	0.0064
ω_1	0.215***	-0.012	0.025	0.111	0.009	-0.0057	0.035	0.036
Variance Equation								
Ω	-8.0020	-1.0054**	-0.68	-4.73**	-0.66	-0.84***	-0.052	-0.74*
Α	0.86***	0.347**	0.282*	0.204	0.195***	0.184	-0.19	0.31
Β	0.086***	-0.132**	0.038	-0.33**	-0.106	-0.204***	-0.29***	-0.133
Γ	-0.60***	0.87***	0.91***	0.32	0.90***	0.88***	0.97***	0.921***
R-square	-0.020	-0.003	0.005	0.021	-0.007	-0.006	-0.005	0.010
R-square Adjusted	-0.029	-0.011	-0.003	0.013	-0.015	-0.015	-0.014	0.0017
AIC[3]	-2.13	-2.73	-2.26	-3.77	-2.23	-3.17	-3.63	-3.03
SIC[4]	-1.99	-2.59	-2.12	-3.63	-2.09	-3.03	-3.49	-2.89

*** 1 Percent, ** 5 Percent, * 10 percent

[3] Akaike info criterion
[4] Schwarz criterion

indicates that the unfavorable news shock does not impact with the same velocity as favorable news does.

Table -C

GJR-GARCH (T-ARCH)

Coefficient	SSE Composite	Hang Seng Index	CNX500	FTSE Bursa	KSE100	STI Index	SE KOSPI 200	SE Weighed TAIEX
Mean Equation								
ω_0	0.017***	0.0072	0.014**	0.0074**	0.0185***	0.007	0.005	0.00541
ω_1	0.051	0.0224	0.0119	0.022	-0.003	0.025	0.046	0.0482
Variance Equation								
Ω	7.91E-04	0.0005*	0.0007	0.00022**	0.0007	0.0003***	0.0006***	0.00021
A	0.1093***	0.117	0.174	0.0176	0.079	-0.0541	-0.173***	0.067
B	0.279***	0.288*	0.011	0.208**	0.173	0.374***	0.489***	0.254
Γ	0.613***	0.628***	0.718***	0.718***	0.746***	0.753***	0.637***	0.711***
R-square	0.024	0.00092	0.00252	0.0060	0.00312	0.0059	0.0041	0.0151
Adjusted R-square	-0.0321	-0.00751	-0.006	-0.00251	-0.0121	-0.0026	-0.0124	0.00671
AIC[5]	-2.25	-2.73	-2.26	-3.81	-2.23	-3.15	-3.59	-3.02
SIC[6]	-2.11	-2.59	-2.12	-3.67	-2.09	-3.01	-3.45	-2.88

*** 1 Percent, ** 5 Percent, * 10 percent

[5] Akaike info criterion

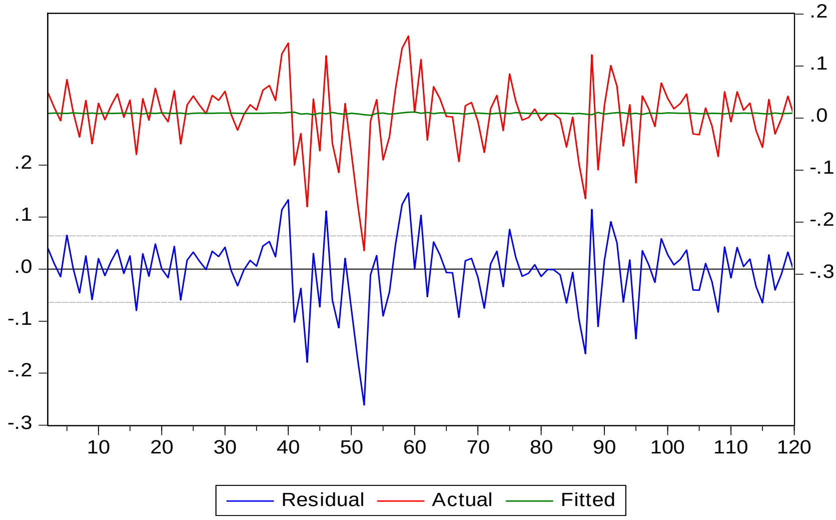
[6] Schwarz criterion

Table C shows GJR-GARCH results. $\alpha - \beta$ is greater than $\alpha + \beta$ in results table in all selected Asian emerging markets except CNX500 (India) index where $\alpha - \beta$ is less compare to $\alpha + \beta$. This shows that negative shocks do not influence in long run on returns. Parameter for GARCH γ is significant in above table in selected indexes at p one percent and shows the leverage which can be confirmed from β value. Negative shocks or unfavorable news influence more on volatility comparative to positive shocks and news especially in the presence of leverage effect. Negative correlation between risk and return is leverage effect which is also a debt-equity ratio. In simple risk goes up then return goes downward. If leverage effect is high that means high debt-equity ratio which ultimately leads to high volatility. So, in the presence of high leverage effect the returns would be lower. GJR-GARCH (TARCH) results are in table C above of our sample indexes. The outcomes are positive and agreeable. In long run interestingly, our outcomes the CNX500 (India), KSE100 (Pakistan) and SE Weighed TAIEX (Taiwan) confirm that there is no leverage effect since our β parameter of each index is not statistically significant. Hang Sang, in long run, shows lesser leverage effect. Interestingly unfavorable news does not have influence in CNX500 (India), KSE100 (Pakistan) and SE Weighed TAIEX (Taiwan) compare to other markets. Except in the above three markets the conditional volatility increases due to unfavorable news. γ, the asymmetric parameter, is significant at probability of 1 percent in all selected indexes and which is quite expected, and this explains impact of good and bad news on t+1 day volatility. If bad news strikes in the market it had more impact on t+1 day that also increases volatility compare to good news. The primarily reason is that γ, the asymmetric parameter, is higher than α, the ARCH parameter of squared residuals. These results also conclude that in long run, KSE100 is an efficient market. The results of this study also show that in order to measure fourth measure of risk kurtosis (leptokurtic kurtosis- Fat-tail) and conditional volatility GJR-GARCH is superior model compare to symmetric GARCH because the selection parameters of a good model AIC and SIC values are low which are required to be low.

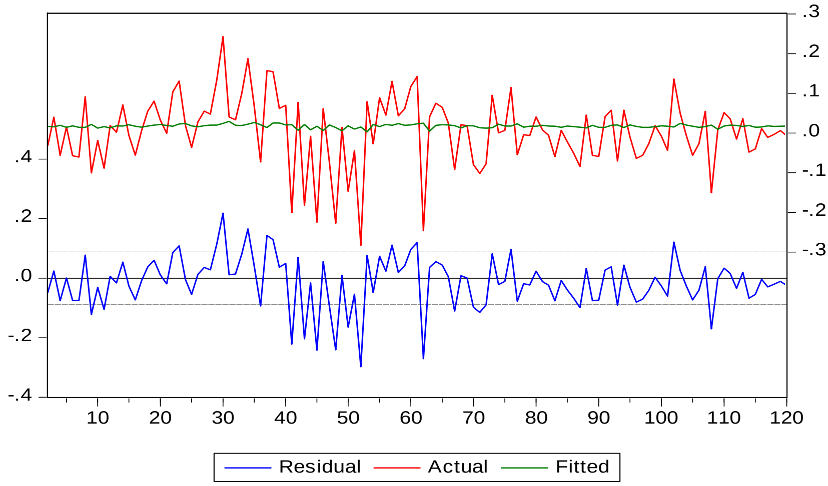
VOLATILITY CLUSTERING EVIDENCE

Figure-A

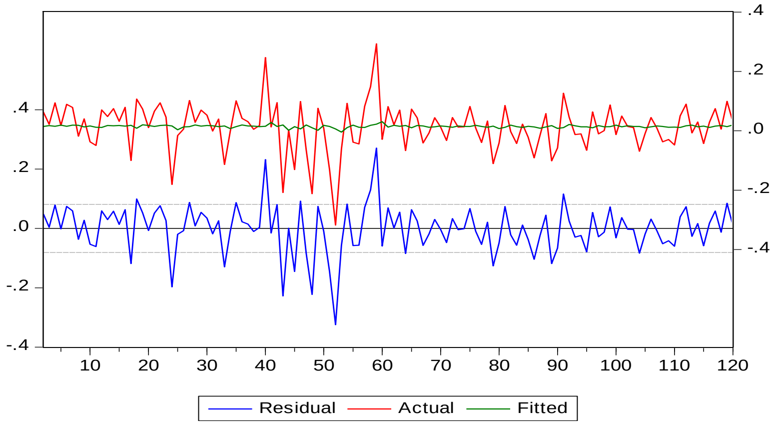
China (SSE Composite index)



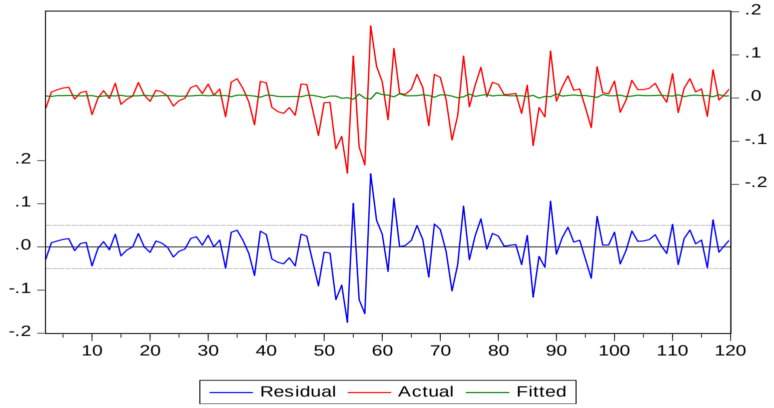
Hong Kong (Hang Seng Index)



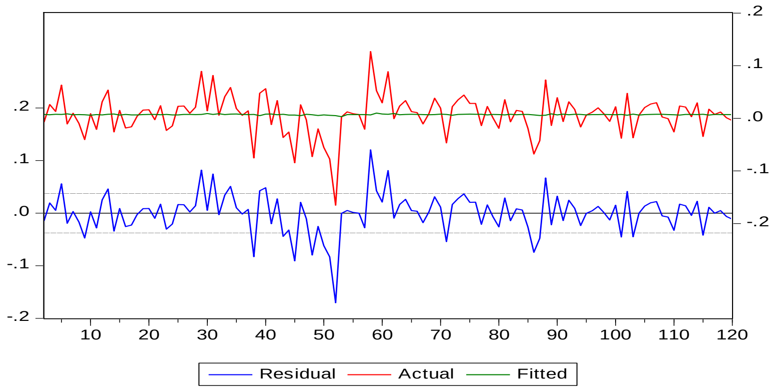
India (CNX500 Index)



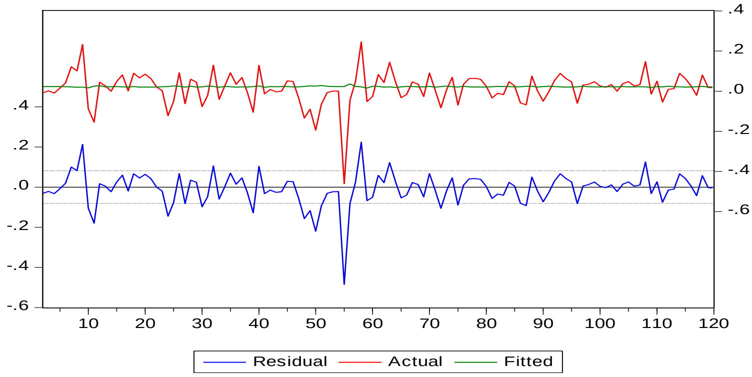
South Korea (SE KOSPI 200 Index)



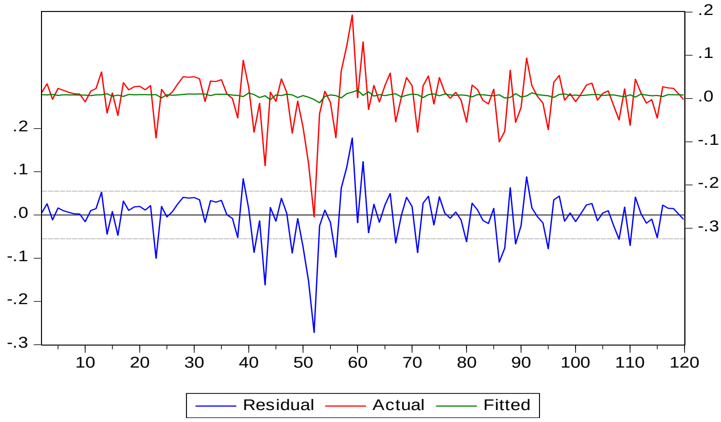
Malaysia (FTSE Bursa Index)



Pakistan (KSE100)



Singapore (Straits Times Index-STI Index)



(SE Weighed TAIEX Index) Taiwan

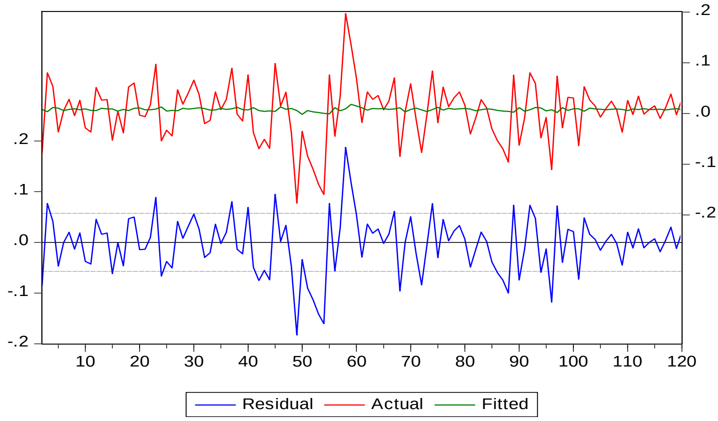


Figure-A shows the test results of sample financial time series and confirms the existence of volatility clustering in the sample markets. The volatility clustering can be seen by looking at figure which shows that periods of low volatility are followed by periods of low volatility for a long time. While periods of high volatility are followed by periods of high volatility from 2009 to 2011 which is also for long time. These persistent fluctuations in residuals of returns strongly favors the argument of presence as well as volatility clustering measurement.

MEASURING ASYMMETRY USING GARCH, GJR-GARCH, AND E-GARCH MODELS

News Impact Curve (NIC) has been used for comprehensive investigation of asymmetric behavior and volatility. To grasp the effect of favorable news (good news) and unfavorable news (bad news) on volatility NIC is used. Many researchers like Bekaert and Wu, (2000), Campbell and Hentschel (1992) and Patton and Sheppard, (2015) have incorporated the idea of good or bad news impact on the volatility risks. To keep information as constant at t-1 and t-2, the implicit relationship can be observed while keeping between G_t and E_{t-1} which is NIC. The basic purpose of NIC's is to show t-1 shocks due to news on t-day volatility and the representation is graphical. This is helpful in drawing and forecasting future volatility from past shocks either positive or negative (E_{t-1}) and that eventually helpful in risk-return measurement.

$$\textbf{GARCH (1,1)} \qquad \mathrm{G_t = A + \alpha_1 E_{t-1}^2} \qquad ------4$$

$$\textit{While} \qquad A = w + \beta_1 \overline{\sigma^2}$$

$$\textit{And} \qquad \bar{\sigma}^2 = \frac{w}{[\,1 - \alpha_1 - \beta_1]}$$

$$\textbf{GJR – GARCH (1,1)} \qquad \mathrm{G_t = A + (\alpha_1 + \gamma_1 I_{t-1}) E_{t-1}^2} \qquad ------5$$

$$\textit{While} \qquad A = w + B_1 \bar{\sigma}^2$$

$$\textit{And} \qquad \bar{\sigma}^2 = \frac{w}{[\,1 - a_1 - B_1 - (\frac{\gamma_1}{2})]}$$

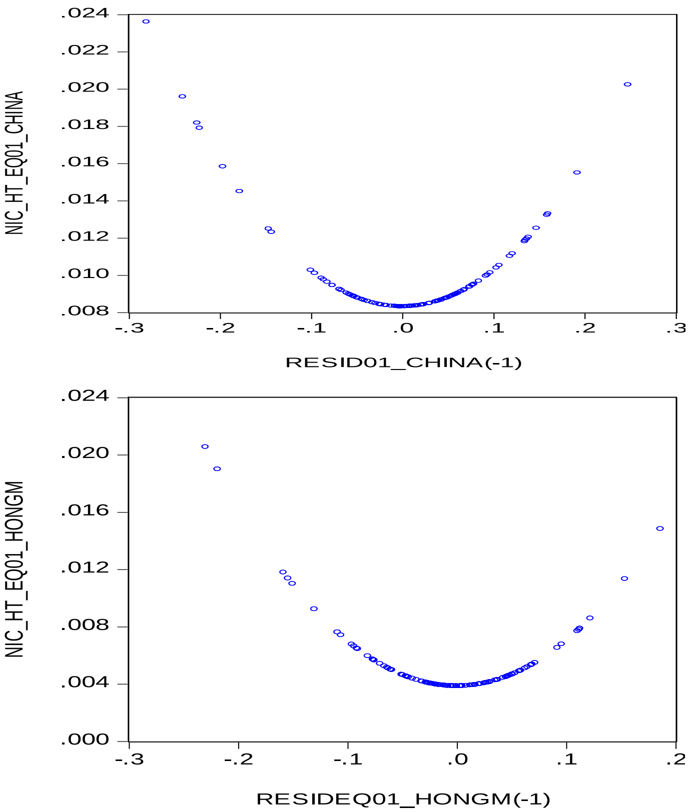
$$\textbf{Exp} - \textbf{GARCH}\ (\mathbf{1},\mathbf{1})\quad G_t = A\exp\left\{\frac{a_1(|E_{t-1}| + \gamma_1 E_{t-1})}{\bar{\sigma}}\right\} \qquad ------6$$

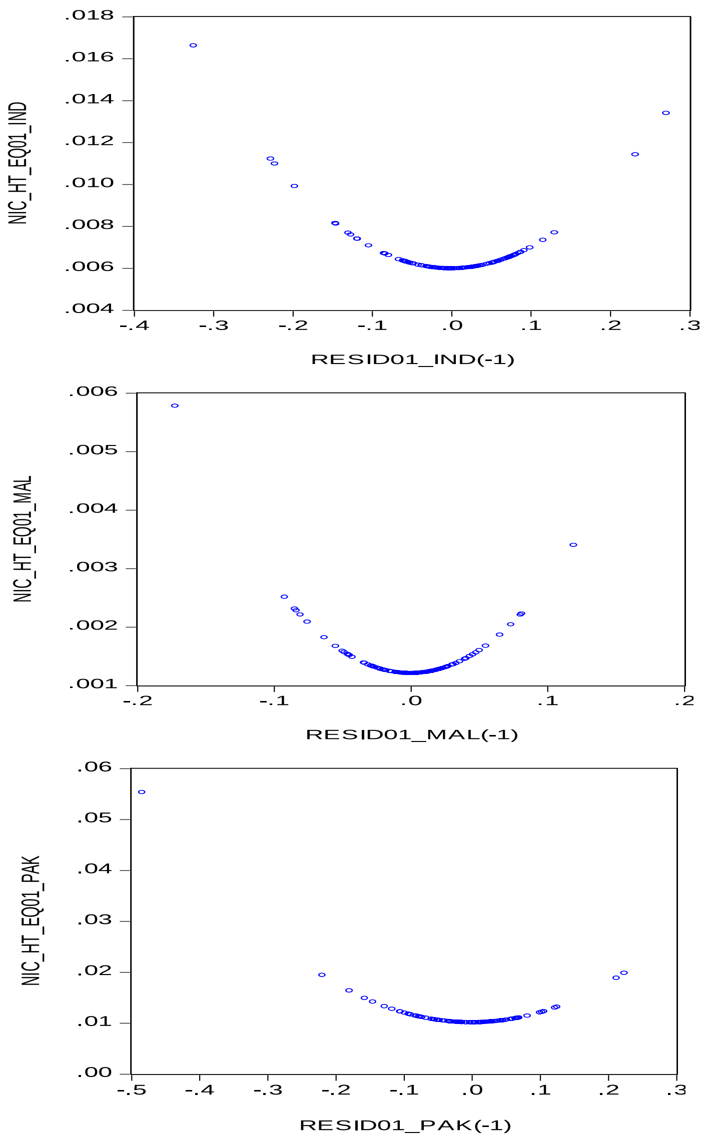
While $A = \bar{\sigma}^2 \beta_1 \exp\,[\omega]$

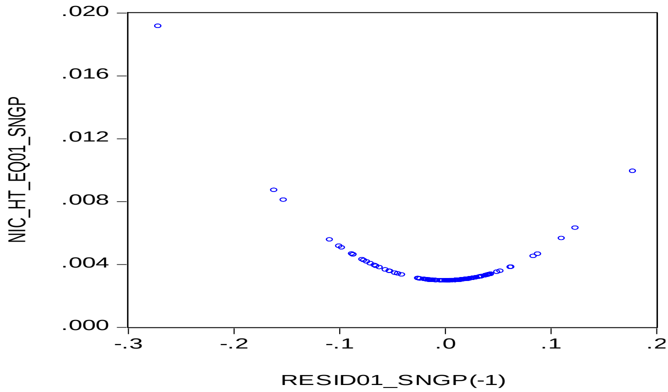
And $\bar{\sigma}^2 = \dfrac{w + a_1\sqrt{2/d}}{1 - B_1}$

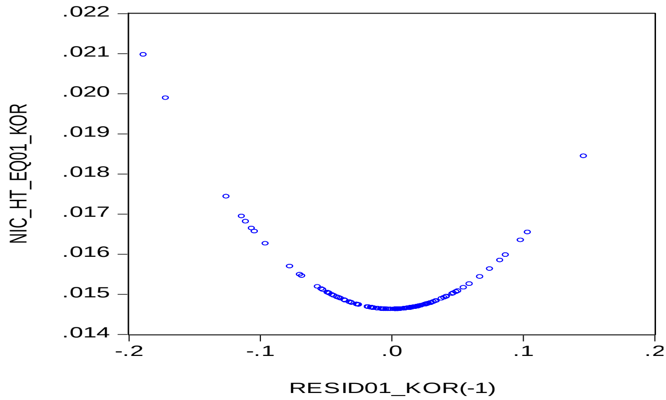
Figure-B

News Impact Curve using Symmetric GARCH model




.018
.016
.014
.012
.010
.008
.006
.004
NIC_HT_EQ01_IND
-.4
-.3
-.2
-.1
.0
.1
.2
.3
RESID01_IND(-1)
.006
.005
.004
.003
.002
.001
NIC_HT_EQ01_MAL
-.2
-.1
.0
.1
.2
RESID01_MAL(-1)
.06
.05
.04
.03
.02
.01
.00
NIC_HT_EQ01_PAK
-.5
-.4
-.3
-.2
-.1
.0
.1
.2
.3
RESID01_PAK(-1)


NIC_HT_EQ01_SNGP
.020
.016
.012
.008
.004
.000
-.3
-.2
-.1
.0
.1
.2
RESID01_SNGP(-1)


NIC_HT_EQ01_KOR
.022
.021
.020
.019
.018
.017
.016
.015
.014
-.2
-.1
.0
.1
.2
RESID01_KOR(-1)

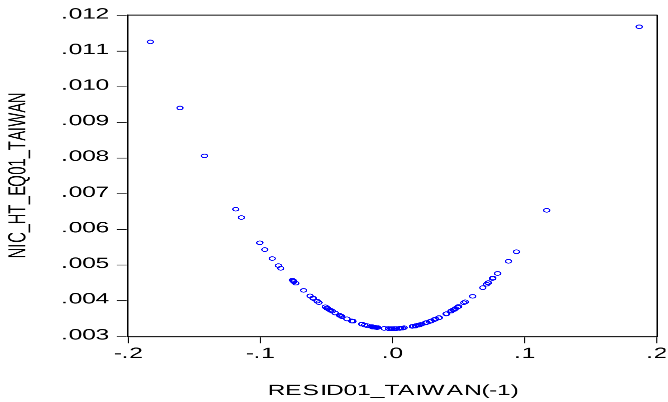
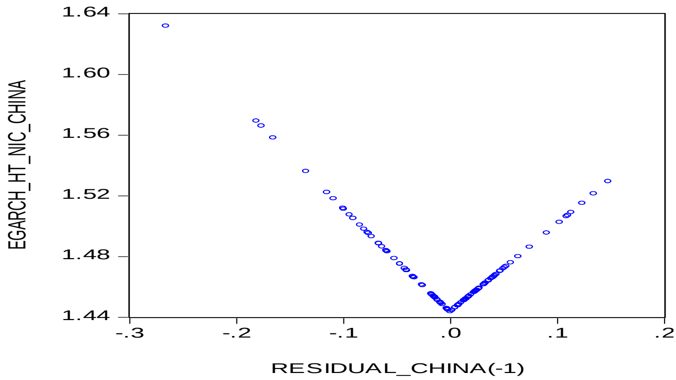
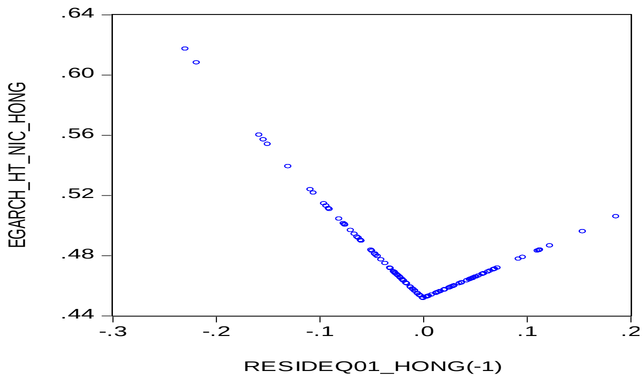
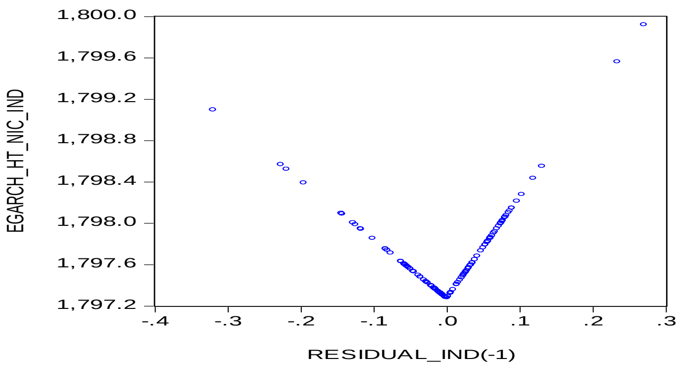

NIC_HT_EQ01_TAIWAN
.012
.011
.010
.009
.008
.007
.006
.005
.004
.003
-.2
-.1
.0
.1
.2
RESID01_TAIWAN(-1)

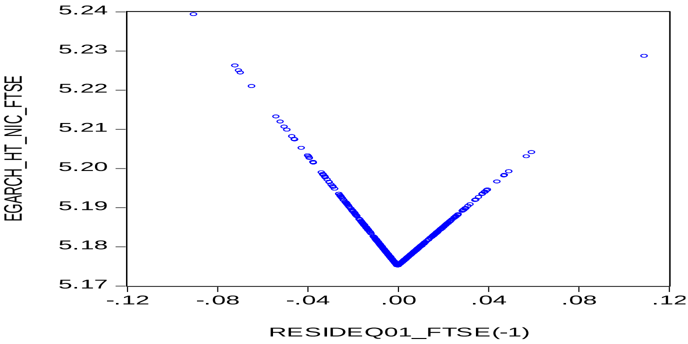
Figure-C

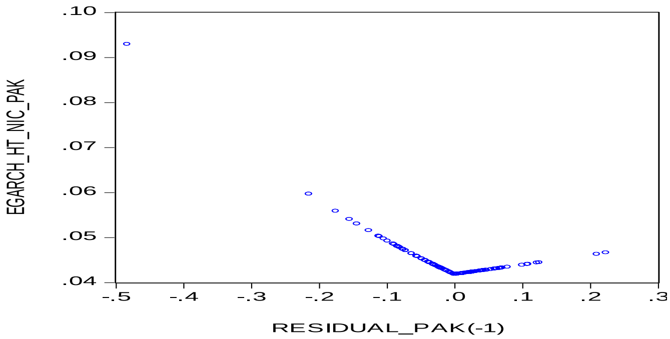
News Impact Curve using Symmetric GARCH model

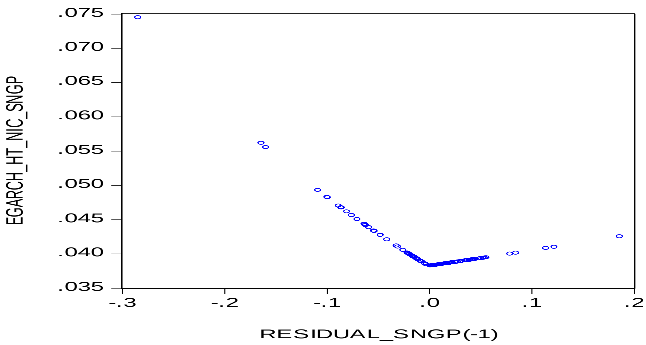


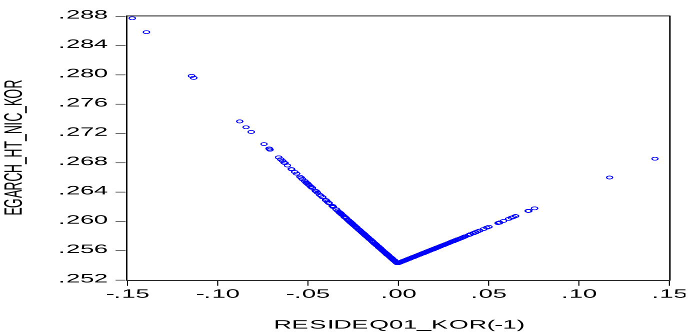





5.24
5.23
5.22
5.21
5.20
5.19
5.18
5.17
EGARCH_HT_NIC_FTSE
-.12
-.08
-.04
.00
.04
.08
.12
RESIDEQ01_FTSE(-1)


.10
.09
.08
.07
.06
.05
.04
EGARCH_HT_NIC_PAK
-.5
-.4
-.3
-.2
-.1
.0
.1
.2
.3
RESIDUAL_PAK(-1)


.075
.070
.065
.060
.055
.050
.045
.040
.035
EGARCH_HT_NIC_SNGP
-.3
-.2
-.1
.0
.1
.2
RESIDUAL_SNGP(-1)


.288
.284
.280
.276
.272
.268
.264
.260
.256
.252
EGARCH_HT_NIC_KOR
-.15
-.10
-.05
.00
.05
.10
.15
RESIDEQ01_KOR(-1)

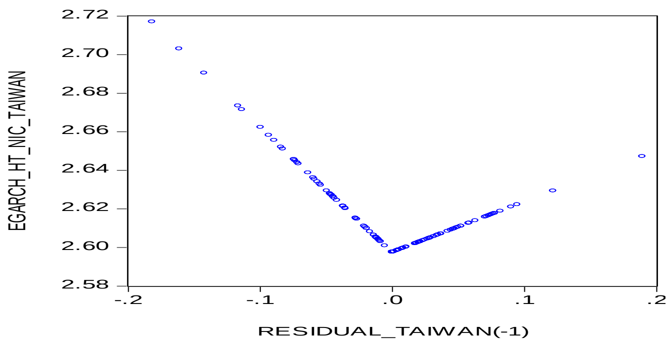
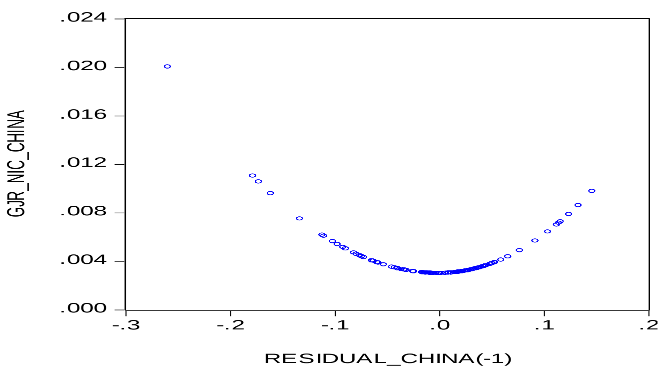
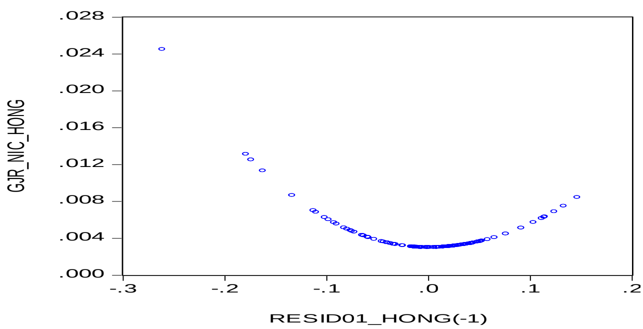
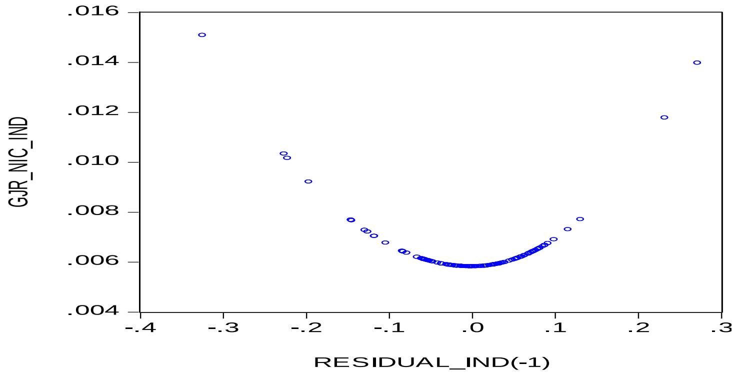


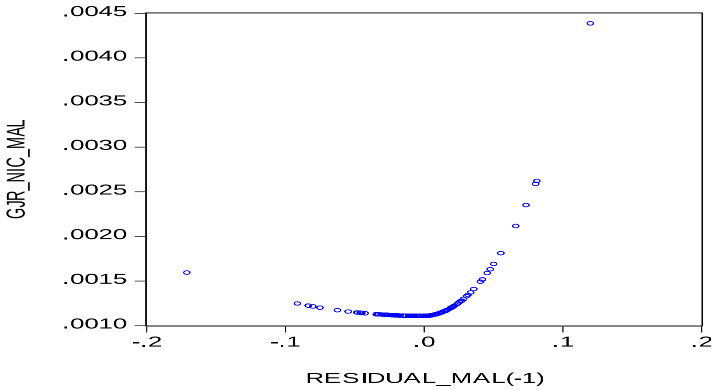
Figure-D

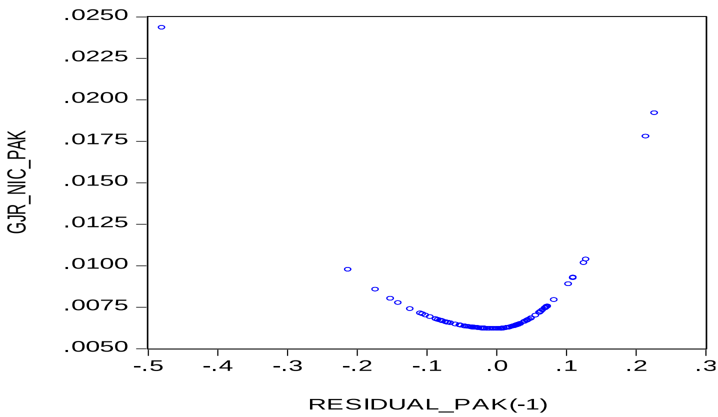
News Impact Curve using asymmetric GJR-GARCH

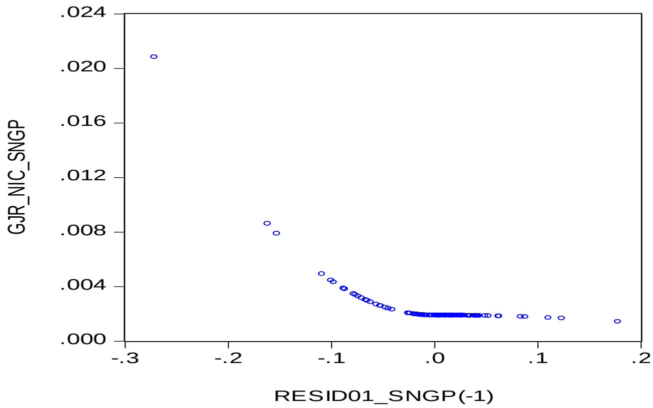


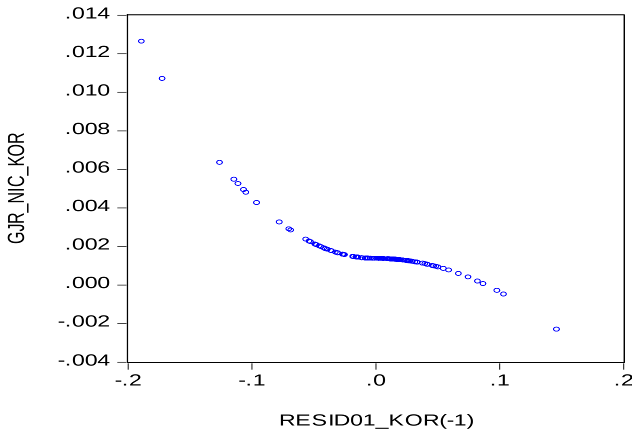


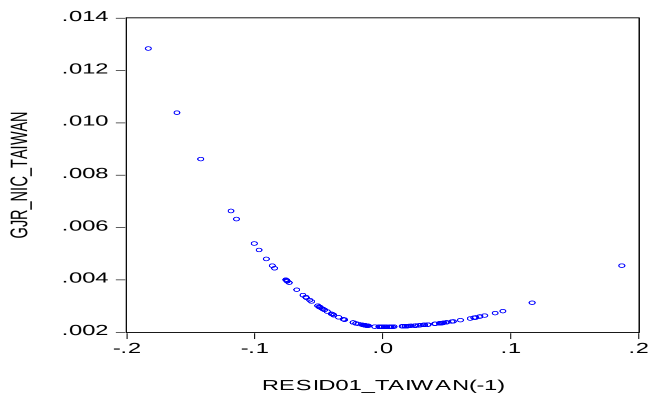

GJR_NIC_IND
.016
.014
.012
.010
.008
.006
.004
-.4
-.3
-.2
-.1
.0
.1
.2
.3
RESIDUAL_IND(-1)


GJR_NIC_MAL
.0045
.0040
.0035
.0030
.0025
.0020
.0015
.0010
-.2
-.1
.0
.1
.2
RESIDUAL_MAL(-1)


GJR_NIC_PAK
.0250
.0225
.0200
.0175
.0150
.0125
.0100
.0075
.0050
-.5
-.4
-.3
-.2
-.1
.0
.1
.2
.3
RESIDUAL_PAK(-1)







Various NICs are shown in the above Figures-B, C and D respectively. These models confirm that the news impact asymmetrically on volatility of financial markets. Above figures confirm this argument.

Asymmetric models predict the future, t+1, t+2, volatility based on bad news and good news and impact of news varies. NIC not only helps to distinguish the velocity of past shocks in the presence of good or bad news on volatility while keeping information of t-2 constant. In this study we try to inspect the possible impact and connection between ϵ_{t-1} $(returns\ shock) and\ variance\ of\ returns$ (σ_t^2), ω is constant. $\alpha_1\ and\ \beta_1$ are our parameters for GJR-GRACH and E-GRACH? In order to estimate the unconditional variance of returns NIC has integrated the lagged, t-1, conditional variance. Based on this we can derive that NIC model's past volatility, t-1, t-2, with current t as well as t+1, t+2, volatility. The shape of the NIC depends on the slope values of bad or good news. Since GARCH (p, q) is a symmetric measure of volatility so the slope values are symmetric or same. On the other hand, looking at asymmetric models, GJR-GARCH and E-GARCH, if $\epsilon_{t-1}\ is\ greater\ than\ 0$ that means a good news and if $\epsilon_{t-1}\ less\ than\ 0$ indicates the presence of bad news while γ is a leverage effect parameter for both asymmetric models. NIC volatility symmetric models result are alike the tested models and confirm our findings are true in sample indexes. The left hand side of Y-axis shows the impact of unfavorable news while right side of Y-axis displays impact of favorable news, the asymmetric shape confirms that unfavorable news has high impact on volatility compare to favorable news.

V. CONCLUSION AND DISCUSSION

This study has emerged with three factual pieces of evidence about financial time series. Evidence one is about the presence of unit root in returns, evidence two is about the presence of volatility clustering and evidence three is about the asymmetric behavior of financial time series. To investigate the evidence one, we run ADF test of Unit Root to check out the presence of stationarity. To check the ARCH effect on returns this research has also applied heteroskedasticity test. The outcomes of both the tests confirm that the data is not only stationary but also has an ARCH effect. Based on evidence one, to check the existence of volatility clustering this study runs various symmetric and asymmetric GARCH, GJR-GARCH, and E-GARCH. The outcomes confirm the existence of volatility clustering in all selected stock markets and investors need to be careful while investing. By summing up α and β parameters of symmetric GARCH we find these are closer to one which shows high clustering volatility and fat-tail risk in sample markets indexes. In asymmetric E-GARCH $\alpha - \beta$ is greater than $\alpha + \beta$ and that endorses the presence of high volatility clusters as well as the effect of leverage. GJR-GARCH also supports the existence of volatility clustering. To investigate evidence three, NIC confirms the existence of asymmetric behavior in all used models. This study concludes that unfavorable news has a severe effect and increases volatility clustering, as well as asymmetry, compare to favorable news. This study tests the prognostic ability of symmetric and asymmetric GARCH models and concludes that asymmetric GARCH models perform better to capture conditional volatility and asymmetric behavior in Asian emerging stock markets. This study can be expendable to other markets e.g. Australia, East Asia, and South American financial markets. By using the broader sample size helps the investors, portfolio managers and policy makers to analyze the existence of level of asymmetric and volatility clustering and make investment and policy decision accordingly. This could be the natural extension to this study and can possible provide commentary over the efficiency of these markets especially in case of good or bad news on time t+1, t+2, from t-1, t-2.

DISCUSSION

This study confirms the volatility clustering and asymmetry presence which are consistence with Ang and Liu (2007), Hashmi and Tay (2007), Ray (2012). The results reveal that volatility clustering is high due to the bad news impact as compare to a good news which also leads to asymmetric and kurtosis risk. The kurtosis and asymmetric risk are confirmed by the presence of volatility clustering and leverage effect which should be taken into consideration while investment making decisions and asset pricing and these are in line with Ang and Liu (2007), and Rossi and Timmermann (2011). The main focus of this study is on the measurement of risk for asset pricing in the presence of additional risks. In case returns are high and volatile then presence of asymmetric risk (skewness) or volatility risk (kurtosis) cannot be denied. The presence of asymmetric risk and volatility clustering risk make returns more volatile and shake out investor confidence. These elements of risks should be considered wisely in construction of portfolios for risk avoider investors and asset pricing. If leverage effect and volatility clustering exist in financial time series then portfolio construction based on men-variance could be miss-leading especially for risk averse investors because these are indications of third (skewness- asymmetry) and fourth (kurtosis- volatility clustering) movements of risk. The presence of third and fourth moments of risk can lead to large positive and negative return and risk forecasting based on mean- variance cannot be reliable. Our results confirm the presence of these higher moment risk. Investor should learn that their returns are not only reward of variance but also of volatility clustering. By ignoring the fact may lead to higher extremes either positive or negative. However, investors would not mind higher positive returns but what if due to these higher moments the investors loss their investment. A must learn lesson for investor could be that ignoring volatility clustering especially in less efficient markets can be fatal.

REFERENCES

Alberg, D., Shalit, H., & Yosef, R. Y. (2008). Estimating stock market volatility using asymmetric GARCH models. Applied Financial Economics, 18, 1201-1208.

Ang, A., & Liu, J. (2007). Risk, returns and dividends. Journal of Financial Economics, 85, 1-38.

Baillie, R. T. (1996). Long memory processes and fractional integration in econometrics. Journal of Econometrics, 73, 5-59.

Beardsley, X., Field, B., & Xiao, M. (2012). Mean-variance-skewness-kurtosis portfolio optimization with return and liquidity. Communications in Mathematical Finance, 1, 13-49.

Bekaert, G., & Wu, G. (2000). Asymmetric volatility and risk in equity markets. The Review of Financial Studies, 13(1), 1-42.

Bollerslev, T. (1986). Generalised autoregressive conditional heterosakadacity. Journal of Economics, 31, 307-327.

Campbell, J. Y., & Hentschel, L. (1992). No news is good news: An asymmetric model of changing volatility in stock returns. Journal of Financial Economics, 31(3), 281–318.

Chen, J., Hong, H., & Stein, J. C. (2001). Forecasting crashes: trading volume, past returns, and conditional skewness in stock prices. Journal of Financial Economics, 61, 345-381.

Christie, A. A. (1982). The stochastic behavior of common stock variances: Value, leverage and interest rate effects. Journal of Financial Economics, 10(4), 407-432.

Engle, R. F., & Ng, V. K. (1993). Measuring and testing the impact of news on volatility. The Journal of Finance, 48(5), 1749–1778.

Fama, E. F. (1965). The behavior of stock-market prices. The Journal of Business, 34(1), 34-105.

Guidolin, M., & Timmermann, A. (2008). International asset allocation under regime switching skew and kurtosis preferences. Review of Financial Studies, 21, 889–935.

Hansen , P., & Lunde, A. (2005). A forecast comparison of volatility models: Does anything beta a GARCH(1,1)? Journal of Applied Econometrics, 20(7), 873-889.

Harvey, C. R., & Siddique, A. (2000). Conditional skewness in asset pricing tests. The Journal of Finance, 55(3), 1263-1295.

Hashmi, A. R., & Tay, A. S. (2007). Global regional sources of risk in equity markets: Evidence from factor models with time-varying conditional skewness. Journal of International Money and Finance, 26, 430-453.

Horváth, L., & Leipus, R. (2009). Effect of aggregation on estimators in AR (1) sequence. Test, 18(3), 546-567.

Horvath, Z., & Johnston, R. (2008). AR (1) Time series process. Econometrics, 1-12.

Horvath, Z., & Johnston, R. (2010). GARCH time series process. Econometrics, 1-25.

Hull, J. c. (2012). Options, futures and other derivatives (8th ed.). Pearson Education, Inc.

Kim, T.-H., & White, H. (2004). On more robust estimation of skewness and kurtosis. Finance Research Letters, 1, 56–73.

Lanne, M., & Saikkonen, P. (2007). Modeling conditional skewness in stock returns. The European Journal of Finance, 13(8), 691-704.

Li, X., Qin, Z., & Kar, S. (2010). Mean-variance-skewness model for portfolio selection with fuzzy returns. European Journal of Operational Research, 202, 239–247.

Liu, Z., Liu, J., & Wang, K. (2013). Measuring co-skewness and co-kurtosis using noisy high frequency financial data. . Journal of Banking and Finance, 1-25.

Lux, T., & Marchesi, M. (2000). Volatility clustering in financial markets: A microsimulation of interacting agents. International Journal of Theoretical and Applied Finance, 4(3), 675-702.

Mandelbrot, B. (1963). The variation of certain speculative prices. The Journal of Business, 36(4), 394-419.

Naqvi, B., Rizvi, K., Mirza, N., & Naqvi, W. A. (2017). Portfolio choices with higher moments of risk at Pakistan Stock Exchange-PSX”. Economic Research Journal, 30(1) 15-31.

Naqvi, S., Rizvi, K., Orangzaib, R., & Ali, M. (2016). Value at risk at Asian emerging equity markets. Science International, 28(4), 311-319.

Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. Econometrica, 59(2), 347-370.

Nelson, D. B., & Foster, D. P. (1994). Asymptotic filtering theory of univariate ARCH model. Econometrica, 62(1), 1-41.

Ning, C., Xu, D., & Wirjanto, T. (2008). Modeling asymmetric volatility clusters using copulas and high frequency data. Finance Research Letters, 5(4), 221-227.

Pagan, A. R., & Schwert, G. (1990). Alternative models for conditional stock volatility. Journal of Econometrics, 45(1-2), 267–290.

Ray, S. (2012). Investigating seasonal behavior in the monthly stock returns: Evidence from BSE Sensex of India. Advances in Asian Social Science, 2(4), 560-569.

Rizvi, S. K., Naqvi, B., Bordes, C., & Mirza, N. (2012). Inflation volatility: An Asian perspective. Munich Personal RePEc Archive, 1-36.

Tseng, J.-J., & Li, S.-P. (2012). Quantifying volatility clustering in financial time series. International Review of Financial Analysis, 23, 1-32.

Wilcox, J., & Fabozzi, F. (2009). A discretionary wealth approach to investment policy. Yale ICF Working Paper No. 09-03, 9(3), 1–43.

APPENDIX-A

Table -I

ADF-Unit Root Test

	SSE composite	Hang Seng Index	CNX500	FTSE Bursa	KSE100	STI Index	SE KOSPI 200	SE Weighed TAIEX
SIC criteria of returns (Lag=13)								
Unit root (ADF) test								
Critical Values	(-11.21)*	(-10.27)*	(-9.52)*	(-9.29)*	(-9.37)*	(-9.34)*	(-10.99)*	(-8.94)*
At 1 percent	-4.04	-3.49	-3.49	-3.49	-3.49	-3.49	-3.49	-3.49
At 5 percent	-3.45	-2.89	-2.89	-2.89	-2.89	-2.88	-2.89	-2.89
At 10 percent	-3.15	-2.58	-2.58	-2.58	-2.58	-2.58	-2.58	-2.58

(*)= $p < 0.05$

Table -II

ARCH Test

	SSE composite	Hang Seng Index	CNX500	FTSE Bursa	KSE100	STI Index	SE KOSPI 200	SE Weighed TAIEX
F-statistic	1.31	23.07	9.63	1.472	0.014	25.61	33.1221	12.1612
Observed R-square	1.25	19.58	9.03	1.483	0.014	21.38	26.2532	11.2112
Probability of F(1,118)	0.0232	0	0.004	0.03	0.0081	0	0	0
Probability of Chi-Square(1)	0.0354	0	0.005	0.22	0.0081	0	0	0