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Modeling Sectoral Stock Indexes Volatility: Empirical Evidence from Pakistan Stock Exchange

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ABTSRACT

Modeling volatility in financial markets is one of the factors that results in direct impact and effect on pricing, risk and portfolio management. This study aims to examine the volatility of stock indices in PSX that include; volatility clustering, fat tails and leptokurtosis behavior. To achieve the objective, ADF unit root test has been performed to check the stationarity and it was concluded from the results that series were stationary at 1st difference. Series taken for this research consists of 11 sectors which includes commercial banks (DCB), cement (DCEM), and chemicals (DCHEM). Fertilizers (DFER), investment banks and investment companies (DIB), insurance (DINS), oil and gas (DOG), power generation and distribution (DPGD), refinery (DREF) and technology and communication (DTC). This study applies; ARCH, GARCH, and EGARCH to evaluate the behavior of share price volatility of Pakistan stock exchange (PSX) covering the period from January 1 2009 through December 31 2016. The main findings suggests that EGARCH or GARCH models are the best fit for all the series as decision making criterion Akaike information criterion (AIC) and Schwarz criterion (SC) are least in these models.

Keywords: Volatility, PSX, Stock Index, ARCH JEL Classification: C22

1. INTRODUCTION

In last few years, the most important area that has gained the attention of most of the researchers and academic scholars and other market analysts is this modeling volatility of financial time series. Many studies have been conducted that determined the best fit model for the investors to make decision for their investments by analyzing the volatility of different sectors outside the Pakistan (i.e., India, Portugal, Jordan, New York etc.). After the black swan events of global recession and 2008 financial crises, Pakistan stock exchange has faced many ups and downs in different sectors on a timely basis with different reasons. As stock index is calculated from the share prices of selected companies by calculating weighted average, we have taken share prices instead of returns of the companies in the sectors and KSE 100 index meeting criterion companies. Stock index (p. stock indices) also known as stock market index is a tool that is used by the investors to gauge the value of stock market's one section to compare it with the other. These sections can be the sectors, group of sectors, or a group of companies that are combined together for their specific features - (e.g., Karachi Stock Exchange Meezan Index (KMI 30) is an index that is formed with a feature of Shariah compliance). Volatility is the fluctuations in the prices of the stocks of different companies either due to demand and supply effect, performance of the companies, or the socio-economic factors of the country. It also refers to the amount of change in the value of security due to risk and uncertainty. Numerous studies have been conducted to test the volatility of stock returns as well as on closing share prices of different stock exchanges other than Pakistan by comparing two stock indices for the different time periods by running the time series and using different methodologies by applying ADF Unit root test and ARCH Family models. But, our problem statement is: "To evaluate the volatility clustering and best fit model (ARCH, GARCH and EGARCH) for the 11 sectors and KSE 100 Index selected from Pakistan stock exchange for the period of 8 years from January 2009 to December 2016." Purpose of the study is to test the volatility clustering and best fit model among all the sectors taken into account along with KSE

100 index. Moreover, it will also be analyzed through ADF unit root test whether the stationarity is at level or at 1st difference. With the probability of Chi-square in descriptive statistics, it will be analyzed whether the ARCH family models are applicable on the given data series or not. In this research paper we have tried to analyze which model will best fit for the investors to predict the volatility between 11 different sectors and KSE 100 index and will allow them to make strategic decisions for their organizations and their own investments by investigating empirically the volatility pattern of stock market of Pakistan based on time series data. Out of 38 sectors the 11 sectors that we have taken are automobile assembler (AA), commercial banks (CB), cement (CEM), chemicals (CHEM), fertilizer(FER), power and gas development (PGD), oil and gas (OG), refinery (REF), insurance (INS), investment banks and Investment companies (IB), technology and communication (TC).

Research objectives of the study are as follow:

- To evaluate the pattern of Pakistani stock market's volatility by using symmetric and asymmetric models.
- To determine the availability of leverage effect in series of daily stock prices of Pakistani stock exchange using asymmetric models.
- To decide the appropriate and best fit ARCH family model on the basis of daily time series stock prices data of Pakistani stock exchange.

2. LITERATURE REVIEW

Modeling the stock prices volatility due to its dynamic performance has a vital importance in finance, in specific investment decision making and in general. The performance behavior has led researchers to put forward numerous statistical and mathematical models to gauge the volatility of stock prices and their returns in global financial markets. The ground breaking studies in this regard are referred to (Engle R. F., 1982) who proposed autoregressive conditional heteroskedasticity (ARCH) model and (Bollerslev, 1986) who proposed an expanded version of ARCH and named it as generalized ARCH model (GARCH). In this section, we will provide you with a brief overview for the empirical findings gathered by the researchers by applying these models on their data of both emerging and developed markets.

Researchers from the earlier time period found that conventional models of time series that have the assumption of constant variance for their operations were not adequate and reliable enough to predict movements of stock returns. Hence, the use of ARCH model that was introduced by (Engle R. F., 1982) that permits the eventual change of conditional variance and making the unconditional variance(s) constant.

Application of ARCH model highlighted the presence of limitations in this model, thus to overwhelm those limitations (Bollerslev, 1986) introduced a new tailored form of model that was generalized ARCH (GARCH) model that permits an extended recall and a more adaptable lag structure. GARCH model not only share the main assumptions about conditional variance (that it is

a specified linear function of past simple variance) with ARCH model, but it also permits the new lagged conditional variances to have an entry in the model too.

It was found on the basis of lowest Akaike information criterion (AIC) and Schwarz criterion (SC) in one of the research that GARCH (1, 1) was the best fit model for explaining volatility clustering and data is stationary at 1% level with the critical value of -3.43. Because of this, the null hypothesis is rejected for all the observations (Karunanithy and Ramachandran, 2015). Similar results were found in another study in year 2016, which showed that null hypothesis is rejected and the data is becoming stationary where ADF unit root test is becoming statistically significant at 1% level as critical value <0.05 (AL-Najjar, 2016).

Methodology used in some of researches were on the basis of negative skewness, volatility clusters, leptokurtosis of the time series data gathered from their respective emerging economies and in addition, they found the similar best fit model for the data was GARCH (1,1) (Rashid and Ahmad, 2008); (Olowe, 2009); (Goudarzi and Ramanarayanan, 2011); (Gökbulut and Pekkaya, 2014).

While in some researches, EGARCH model was found best fit model for detecting leverage effect, leptokurtosis, and measuring volatility clustering effect for the daily stock returns of different countries' stock data (Awartani and Corradi, 2005); (Floros, 2008); (Yalama and Sevil, 2008); (Emenike, 2010); (Su, 2010); (Miron and Tudor, 2010); (Angabini and Wasiuzzaman, 2011); (Abd Elaal, 2011); (Ezzat, 2012).

3. RESEARCH METHODOLOGY

Quantitative study was the basis of our study which followed post positivism philosophy along with the number crunches and the deductive approach was used. Strategy of our study was of explanatory nature as we tried to test the volatility clusters, stationarity and best fit model among the above mentioned sectors and KSE 100 index. Mono method had been used because we gathered the data from different secondary sources our study is based on time series data. We used descriptive statistics techniques, ADF unit root test at level and at 1st difference and ARCH, GARCH and EGARCH model in EVIEWS to find out the best fit model for each of the series taken into consideration for each sector. Our sample is solely based on the secondary data from (www.khistocks. com) website. We chose non-probability sampling method and within this, convenience based sampling method. 11 sectors along with KSE 100 index have been chosen because the data was available for these sectors from the time period January 2009 to December 2016 without any missing figures to perform better analysis and best fit model for each sector about volatility clustering.

3.1. Research Models

Models which have been used in this research paper are 4 models which include ADF unit root test model, ARCH model, GARCH

model and EGARCH model. Following is the mathematical explanation of each model separately.

3.1.1. ADF unit root test model

The presence of unit root in a time series is tested using Augmented Dickey- Fuller test. It tests for a unit root in the univariate representation of time series (Dickey and Fuller, 1979). For a price series P_t , the ADF test consists of a regression of the first difference of the series against the series lagged k times as follows:

$$\Delta P_{t} = \alpha + \delta P_{t-1} + \rho \sum_{i-1} \beta_{i} \Delta P_{t-1} + E_{T}$$
(1)

If the ADF test rejects the null hypothesis of a unit root in the price series, that is if the absolute value of ADF statistics exceeds the McKinnon critical value the series is stationary but if it is not stationary at level so we will go with 1st difference and we can continue to analyze the series.

After checking for unit root and before estimating a full ARCH model for a financial time series, it is necessary to check for the presence of ARCH effects in the residuals. If there are no ARCH effects in the residuals, then the ARCH model is unnecessary and unspecified. After checking for unit root and detecting the ARCH effects we can specify asymmetric GARCH model to test the leverage effects.

3.1.2. GARCH model

The GARCH model (Bollerslev, 1986) which allows the conditional variance to be dependent upon previous own lags; conform to the conditional variance equation in the simplest form as:

Mean equation:
$$p_t = \mu + \varepsilon_t$$
 (2)

Variance equation:
$$\sigma_t^2 = \omega + \alpha_1 \varepsilon \frac{2}{t-1} + \beta_1 \sigma \frac{2}{t-1}$$
 (3)

Where $\omega > 0$, $\alpha_1 \ge 0$, $\beta_1 \ge 0$, and P_t is the price of the asset at time *t*, μ is the average price, and E_T is the residual price.

The size of parameters α and β determine the short-run dynamics of the volatility time series. If the sum of the coefficient is equal to one, then any shock will lead to a permanent change in all future values. Hence, shock to the conditional variance is "persistence."

3.1.3. EGARCH model

$$\operatorname{Ln}(\sigma \frac{2}{t}) = \omega + \beta_{1} \operatorname{Ln}(\sigma \frac{2}{t}) + \alpha_{1} \left\{ \left| \varepsilon_{t-1} \div \sigma_{t-1} \right|_{-} \sqrt{2} \div \pi \right\}_{-}$$

$$\gamma \varepsilon_{t-1} \div \sigma_{t-1}$$

$$(4)$$

It is evident from the above equation that a negative shock increases future volatility or uncertainty while a positive shock eases the effect on future uncertainty. In macroeconomic analysis, financial markets and corporate finance, a negative shock usually implies bad news, leading to a more uncertain future. Consequently, for example, shareholders would require a higher expected return to compensate for bearing increased risk in their investment. This is an EGARCH (1, 1) model.

3.2. Data Collection Method and Instrument

Data collection method used for this study is similar to the other studies which is mono as we have gathered data from (www. khistocks.com) as it provided the closing share prices of each sector from the time period January 2009 to December 2016 and that data was exported to Excel which is merged for the further data analysis.

3.3. Hypotheses

 H_1 : There is no ARCH, GARCH and EGARCH effect in DAA, DCB, DCEM, DCHEM, DIB, DFER, DOG, DKSE, DREF, DPGD, DTC and DINS.

H₂: Data is not stationary at level or at 1st difference at each series.

3.4. Plan of Analysis/Statistical

Statistical tools and plan of analysis used for this study was time series data techniques, descriptive statistics, ADF unit root test at level and at 1st difference, Heteroskedasticity test ARCH, GARCH and EGARCH models.

4. RESULTS AND ANALYSIS

Analysis has been done on 11 sectors such as commercial banks (DCB), cement (DCEM), and chemicals (DCHEM). Fertilizers (DFER), investment banks and investment companies (DIB), insurance (DINS), oil and gas (DOG), power generation and distribution (DPGD), refinery (DREF) and technology and communication (DTC) along with overall KSE 100 index (DKSE) from the time period 01/01/2009–31/12/2016 which contains 1978 observations for the consecutive last 8 years. Data has been analyzed through descriptive statistics, unit root level testing and 1st difference testing to check the stationary for each series of sector. Moreover, ARCH, GARCH and EGARCH models have applied to check the volatility clustering and leptokurtosis from the descriptive statistics (Table 1).

The results show that data is at stationarity while performing ADF unit root test at 1st difference as P < 5% (Table 2). It has given an indication that ARCH Family models can be performed to check the volatility between the series. It can be concluded from the above results that null hypothesis is rejected at all the 12 tested Series followed by 3 model testing which includes ARCH effect test, GARCH effect test and EGARCH effect test as P < 5% except DCEM series at GARCH effect test, DCHEM series at GARCH effect test, and DTC series at both GARCH and EGARCH effect tests because their p-values are more than 5% so in this case null hypothesis will be accepted. Moreover, best fit model decision has been taken on the basis of 2 criterion i.e. lowest AIC and SC which is in accordance with the methodology of (Karunanithy and Ramachandran, 2015).

4.1. Graphical Representation of ADF Unit Root Test Results is as Follows

Graph 1 shows the volatility clustering of the indexes for each of the sectoral series in a group. It shows that higher changes will be followed by higher changes and lower changes will result in

Table 1: "Descriptive statistics"

Series	Mean	Median	Maximum	Minimum	SD	Observations
KSE	20661.06	16797.95	47806.97	4815.34	10978.05	1978
AA	2397.317	1263.905	9913.19	375.1	2155.743	1978
CB	4521.427	3547.83	9628.02	1311.6	2182.164	1978
CEM	2499.31	1490.645	8710.62	510.16	2144.227	1978
CHEM	1501.639	1524.265	3147.21	550.29	478.574	1978
FER	3671.909	3608.41	8755.18	401	2753	1978
IB	89.1648	77.56	297.25	23.31	45.12759	1978
INS	445.8601	296.46	1051.13	164.25	270.2442	1978
OG	2929.356	2830.365	4941.89	951.41	748.9765	1978
PGD	3613.371	3074.405	8318.92	815.24	2199.86	1978
REF	852.0839	747.85	1972.37	253.62	364.6164	1978
TC	735.4991	647	1508.72	243.65	320.2859	1978
	Skewness	Kurtosis	Jarque-Bera	Probability	Sum	Sum Sq. Dev.
KSE	0.409525	1.78511	176.9321	0.00	40867568	2.38E+11
	0.409525	1./0./11	170.7521	0.00	4000/300	2.30E+11
AA	1.385009	4.273705	766.0895	0.00	4741893	9.19E+09
AA CB						
	1.385009	4.273705	766.0895	0.00	4741893	9.19E+09
CB	1.385009 0.370628	4.273705 1.530041	766.0895 223.3689	0.00 0.00	4741893 8943382	9.19E+09 9.41E+09
CB CEM	1.385009 0.370628 0.931627	4.273705 1.530041 2.59706	766.0895 223.3689 299.5084	0.00 0.00 0.00	4741893 8943382 4943635	9.19E+09 9.41E+09 9.09E+09
CB CEM CHEM	1.385009 0.370628 0.931627 0.192179	4.273705 1.530041 2.59706 3.460957	766.0895 223.3689 299.5084 29.68754	0.00 0.00 0.00 0.00	4741893 8943382 4943635 2970242	9.19E+09 9.41E+09 9.09E+09 4.53E+08
CB CEM CHEM FER	1.385009 0.370628 0.931627 0.192179 0.361682	4.273705 1.530041 2.59706 3.460957 1.597466	766.0895 223.3689 299.5084 29.68754 205.2469	0.00 0.00 0.00 0.00 0.00	4741893 8943382 4943635 2970242 7263036	9.19E+09 9.41E+09 9.09E+09 4.53E+08 1.50E+10
CB CEM CHEM FER IB	1.385009 0.370628 0.931627 0.192179 0.361682 1.080215	4.273705 1.530041 2.59706 3.460957 1.597466 3.84608	766.0895 223.3689 299.5084 29.68754 205.2469 443.6747	0.00 0.00 0.00 0.00 0.00 0.00 0.00	4741893 8943382 4943635 2970242 7263036 176368	9.19E+09 9.41E+09 9.09E+09 4.53E+08 1.50E+10 4026159
CB CEM CHEM FER IB INS	1.385009 0.370628 0.931627 0.192179 0.361682 1.080215 0.716137	4.273705 1.530041 2.59706 3.460957 1.597466 3.84608 1.85858	766.0895 223.3689 299.5084 29.68754 205.2469 443.6747 276.4462	$\begin{array}{c} 0.00\\ 0.00\\ 0.00\\ 0.00\\ 0.00\\ 0.00\\ 0.00\\ 0.00\\ 0.00\\ \end{array}$	4741893 8943382 4943635 2970242 7263036 176368 881911.4	9.19E+09 9.41E+09 9.09E+09 4.53E+08 1.50E+10 4026159 1.44E+08
CB CEM CHEM FER IB INS OG	1.385009 0.370628 0.931627 0.192179 0.361682 1.080215 0.716137 -0.11185	4.273705 1.530041 2.59706 3.460957 1.597466 3.84608 1.85858 2.696685	766.0895 223.3689 299.5084 29.68754 205.2469 443.6747 276.4462 11.70683	$\begin{array}{c} 0.00\\ 0.00\\ 0.00\\ 0.00\\ 0.00\\ 0.00\\ 0.00\\ 0.00\\ 0.00\\ 0.00287\end{array}$	4741893 8943382 4943635 2970242 7263036 176368 881911.4 5794267	9.19E+09 9.41E+09 9.09E+09 4.53E+08 1.50E+10 4026159 1.44E+08 1.11E+09

Findings: Average share prices (mean) of all the sectors (series) is ranging from 89 to 4521 which shows that the lowest mean is coming in investment banks (89.1648) whereas; highest mean consists of consumer banking (4521.427) whereas KSE 100 index has mean of 20661.06. Kurtosis of automobile assembler, chemicals, investment banks and investment companies and refinery are more than 3 which shows that there lies leptokurtosis whereas remaining sectors do not have leptokurtosis. Jarque-Bera shows value more than 5 which mean the observations are not normally distributed. Probability of Chi-square is<5% which shows that the ARCH effect will be strongly evident in these series and we can perform the ARCH family models to test the volatility

SD: Standard deviation

Table 2: "Results of ADF unit root test"

Series	Stationary results	Hypothesis
DAA	The series is at stationary at first difference 1 (1)	Reject null hypothesis
DCB	The series is at stationary at first difference 1 (1)	Reject null hypothesis
DCEM	The series is at stationary at first difference 1 (1)	Reject null hypothesis
DCHEM	The series is at stationary at first difference 1 (1)	Reject null hypothesis
DFER	The series is at stationary at first difference 1 (1)	Reject null hypothesis
DIB	The series is at stationary at first difference 1 (1)	Reject null hypothesis
DINS	The series is at stationary at first difference 1 (1)	Reject null hypothesis
DKSE	The series is at stationary at first difference 1 (1)	Reject null hypothesis
DOG	The series is at stationary at first difference 1 (1)	Reject null hypothesis
DPGD	The series is at stationary at first difference 1 (1)	Reject null hypothesis
DREF	The series is at stationary at first difference 1 (1)	Reject null hypothesis
DTC	The series is at stationary at first difference 1 (1)	Reject null hypothesis

smaller changes. Bad news will have greater impact than that of the good news. The graphs with either updward or downward trends are nonstationary and the graphs with volatility clustering are after stationary testing and kept at 1st difference according to Augmented Dickey Fuller test results in order to compare the volatility clustering and fat tails.

From the results, it can be concluded that in most of the series both AIC and SC are lowest at either EGARCH and GARCH so GARCH and EGARCH are the best fit models except in DPGD series in which AIC was lowest in EGARCH and SC was lowest in GARCH model (Table 3). Results showing GARCH effect model fits best are in accordance with the findings of (Karunanithy and Ramachandran, 2015), (Rashid and Ahmad, 2008), (Olowe, 2009), (Goudarzi and Ramanarayanan, 2011) and (Gökbulut and Pekkaya, 2014) whereas: Results showing EGARCH model fits best are similar to the findings of (Awartani and Corradi, 2005), (Floros, 2008), (Yalama and Sevil, 2008), (Emenike, 2010), (Su, 2010), (Miron and Tudor, 2010), (Abd El, 2011) and (Ezzat, 2012).

5. CONCLUSION AND RECOMMENDATIONS

5.1. Conclusion

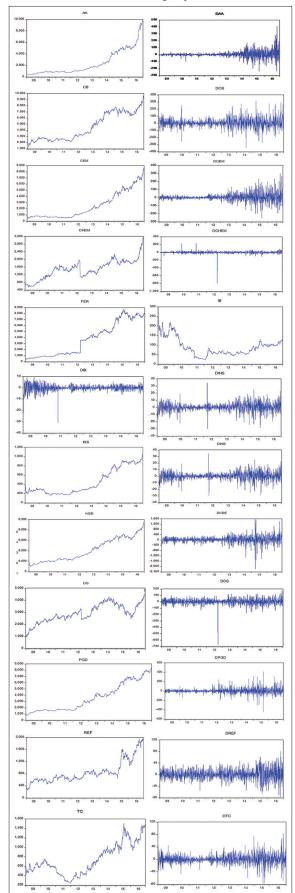
Modeling volatility in financial markets is one of the factors that results in direct impact and effect on pricing, risk and portfolio

Table 3.	Table 3. ARCH Family Models						
Series	ARCH	GARCH	EGARCH	Model fit results			
DAA							
AIC	9.629414	8.814718	8.806796	EGARCH is the best fit model on the basis of lowest AIC and lowest SC in DAA series			
SC	9.637896	8.826027	8.820932				
DCB							
AIC	10.80182	10.6298	10.61911	EGARCH is the best fit model on the basis of lowest AIC and lowest SC in DCB series			
SC	10.8103	10.64111	10.63325				
DCEM							
AIC	10.039	9.302861	9.302908	GARCH is the best fit model on the basis of lowest AIC and lowest SC in DCEM series			
SC	10.04748	9.31417	9.317044				
DCHEM							
AIC	9.521926	9.127099	9.506421	GARCH is the best fit model on the basis of lowest AIC and lowest SC in DCHEM series			
SC	9.530408	9.138408	9.520557				
DFER							
AIC	11.29621	11.29579	10.77226	EGARCH is the best fit model on the basis of lowest AIC and lowest SC in DFER series			
SC	11.30469	11.3071	10.7864				
DIB							
AIC	4.365486	4.214897	4.20442	EGARCH is the best fit model on the basis of lowest AIC and lowest SC in DIB series			
SC	4.373968	4.226206	4.218556				
DINS							
AIC	6.040142	5.795182	5.79036	EGARCH is the best fit model on the basis of lowest AIC and lowest SC in DINS series			
SC	6.048624	5.80649	5.804496				
DKSE							
AIC	13.35385	13.0994	13.07897	EGARCH is the best fit model on the basis of lowest AIC and lowest SC in DKSE series			
SC	13.36234	13.11071	13.09311				
DOG							
AIC	9.963538	9.932542	9.902034	EGARCH is the best fit model on the basis of lowest AIC and lowest SC in DOG series			
SC	9.972019	9.94385	9.91617				
DPGD							
AIC	10.50548	10.14702	10.14689	EGARCH is the best fit model on the basis of lowest AIC and GARCH model is best fit on			
				the basis of lowest SC in DPGD series			
SC	10.51396	10.15833	10.16102				
DREF							
AIC	8.318086	8.173142	8.177206	GARCH is the best fit model on the basis of lowest AIC and lowest SC in DREF series			
SC	8.326567	8.184451	8.191342				
DTC							
AIC	7.998878	7.787176	7.778189	EGARCH is the best fit model on the basis of lowest AIC and lowest SC in DTC series			
SC	8.007359	7.798485	7.792324				

management. This study aims to examine the volatility of stock indices in PSX that include; volatility clustering, fat tails and leptokurtosis behavior. The results show that data is at stationarity while performing ADF unit root test at 1^{st} difference as P < 5%. It has given an indication that ARCH family models can be performed to check the volatility between the series. It can be concluded from the above results that null hypothesis is rejected at all the 12 tested series followed by 3 model testing which includes ARCH effect test, GARCH effect test and EGARCH effect test as P < 5% except DCEM series at GARCH effect test, DCHEM series at GARCH effect test, DIB series at EGARCH effect test and DTC series at both GARCH and EGARCH effect tests because their P-values are more than 5% so in this case null hypothesis will be accepted. Moreover, best fit model decision has been taken on the basis of 2 criterion i.e. lowest AIC and SC which is in accordance with the methodology of (Karunanithy and Ramachandran, 2015).

From the above results, it can be concluded that in most of the series both AIC and SC are lowest at either EGARCH and GARCH so GARCH and EGARCH are the best fit models except in DPGD series in which AIC was lowest in EGARCH and SC was lowest in GARCH Model (Table 3). Results showing GARCH effect model fits best are in accordance with the findings of (Karunanithy and Ramachandran, 2015), (Rashid and Ahmad, 2008), (Olowe, 2009), (Goudarzi and Ramanarayanan, 2011) and (Gökbulut and Pekkaya, 2014) whereas: Results showing EGARCH model fits best are similar to the findings of (Awartani and Corradi, 2005), (Floros, 2008), (Yalama and Sevil, 2008), (Emenike, 2010), (Su, 2010), (Miron and Tudor, 2010), (Abd Elaal, 2011) and (Ezzat, 2012).

After analysing the results, it can be recommended to the investors to invest in Investment banks and investment companies sector as it is more lucrative option for them on the basis of lowest AIC and SC and EGARCH model fits best in it. EGARCH model recommends that there is low leverage effect which means the investment sector is more relying on equity financing so this will attract the investors to invest in this sector to get more returns and they are less risky too. New researchers will have an edge to work on more sectors and stock indices to check the volatility and risk factors for different time periods and using different methodologies to research on their own countries' stock indices as well as in comparison with the



Graph 1: Volatility clustering of the indexes for each of the sectoral series in a group

other country's stock indices to have better understanding of fluctuations in their stock market.

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