

## Time Series Analysis of Stock Market Volatility in Pakistan

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### Authors' contributions

This work was carried out in collaboration among all authors. Author TR designed the study, wrote the protocol and wrote the first draft of the manuscript. Author AI solely completed the analysis section. Author KR contributed in writing the results, literature searches and improved the overall standard of the paper. All authors read and approved the final manuscript.

### Article Information

DOI: 10.9734/AJPAS/2020/v6i430166

#### Editor(s):

(1) Dr. Oguntunde, Pelumi Emmanuel, Department of Mathematics, College of Science and Technology, Covenant University, Ota, Ogun State, Nigeria.

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Complete Peer review History: <http://www.sdiarticle4.com/review-history/54416>

Received: 01 December 2019

Accepted: 06 February 2020

Published: 15 February 2020

Original Research Article

## Abstract

The stock market in an emerging country like Pakistan has been volatile from the earliest times. This paper studies the volatility of Pakistan Stock Exchange (PSX) (using Karachi Stock Exchange 100 Index (KSE-100) as a proxy) through the application of Generalized Autoregressive Conditional Heteroscedasticity (GARCH) family models.

The sample period consists of 4831 daily observations for the 19 year trading period (from 2000 to 2019). Symmetric GARCH (2, 1), asymmetric EGARCH (1, 1), GJR-GARCH (1, 1) and APARCH (1, 1) models were used under Gaussian distributional assumptions. The results validate the empirical findings of previous studies conducted in Pakistan that log returns of KSE-100 Index are characterized by volatility clustering, time-variability, leptokurtic distribution with dominant ARCH and GARCH effects. An interesting feature of Pakistan Stock Exchange revealed by asymmetric models (used in the study) is that PSX is more volatile to good news than bad news. Moreover EGARCH (1, 1) outperforms all other models of the study on the basis of AIC/BIC criterion. However the comparison of correlations of variances predicted by three asymmetric models reveal that correlations among them are very high, with minimum correlation being 98%. This essentially means that all three asymmetric models provide a good fit to PSX.

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*Keywords: GARCH family models; Pakistan; asymmetry; volatility.*

## 1 Introduction

The financial assets prices are considered random variables for the purpose of financial analysis although the preference is for financial asset returns rather than asset prices. Most financial studies involve returns, instead of prices of assets. Tsay [1] mentioned that Campbell, Lo, and MacKinlay [2] advocated the usage of returns because it is a complete and scale-free summary of the investment opportunity and return series have more attractive statistical properties giving it an edge over price series.

A financial time series like stock return series is produced by taking log returns of the stock over the study period. Financial time series includes not just stock return series but also exchange rate series, interest rate series, option price series etc. Traditional econometric models such as regression analysis have underlying assumption of unchanged variance (homoscedasticity). This assumption is incorrect as financial time series is proven to have variance which varies (heteroscedasticity). Apart from heteroscedasticity, researchers have also concluded many distinguishing characteristics (called stylized facts) of financial time series. It has excess kurtosis, exhibits volatility clustering and has leverage effects.

Traditional econometric models being ineffective in case of financial data resulted in efforts of scholars to find new models for financial time series. In 1982, Engle first proposed the ARCH (Auto-Regressive Conditional Heteroscedastic) for modelling the error of variance. This model solved the heteroscedasticity problem but it required a large order  $q$  to estimate conditional variance. In 1986, Bollerslev solved the problem of many lags of ARCH model by introducing the generalized ARCH model, namely GARCH (generalized autoregressive conditional heteroscedasticity) model. Thereafter, a number of scholars expanded various models similar with GARCH model, such as IGARCH, EGARCH, TARARCH, GJR-GARCH, APARCH, GARCH-M and VGARCH (to name a few) forming a GARCH model family. The univariate volatility models, which are discussed in this paper are the autoregressive conditional heteroscedastic (ARCH) model of Engle [3], the generalized ARCH (GARCH) model of Bollerslev [4], exponential GARCH (EGARCH) model of Nelson [5], GJR from threshold GARCH of Glosten, Jagannathan and Runkle [6], and Asymmetric power ARCH (APARCH) model (1993) of Ding, Granger and Engle [7].

The findings of this study indicate a high degree of persistence in the volatility of stock returns on the PSX. The response to news arrival is also asymmetrical as good news causes more volatility than the bad news. The three asymmetrical GARCH models (EGARCH, GJR-GARCH and APARCH) validate the presence of leverage effect in Pakistan Stock Exchange. AIC/BIC criterion pick EGARCH as the best model but the analysis of correlations among variances predicted by the three asymmetrical models show that variances are highly correlated.

The paper is organized as follows. Section 1 includes introduction, Section 2 includes Literature Review, Section 3 is Trend Analysis of KSE 100 Index, and Section 4 is data description, Methodology and Results. Conclusion is provided in section 5.

## 2 Literature Review

It is a well-known fact that developed markets and Emerging Markets have their own structural dimensions. The emerging markets have many imperfections. This includes weak regulatory framework, shallow markets which are dominated by few market makers and market activity being concentrated in few major shares, asymmetric information, speculative trading and marginal presence of small investor. There is an enormous body of research that applies GARCH and ARCH models in capturing the stock market volatility. These studies span over alternate regions.

Srinivasan [8] did modelling of the volatility of the S&P 500 Index returns of United States stock market and found the leverage effect to be present. Danielson [9] found EGARCH (2, 1) model performed better than ARCH (5), GARCH (1, 2) and IGARCH (1, 1, 0) on daily data of S&P 500 Index from 1980 to 1987. Guidi [10] compared several GARCH models to model volatility of German, Swiss and UK stock market indexes. The results revealed that all GARCH models provided evidence of asymmetric effects. Tse [11] examined the stock returns volatility in the Tokyo Stock Exchange and found that the returns series exhibited significant ARCH and GARCH effects with the time series also showing significant non-normality.

Gokcan [12] found that for emerging stock markets the GARCH (1, 1) model performed better in volatility prediction of time series data. Lim and Sek [13] modelled the volatility of stock market in Malaysia and established symmetric and asymmetric GARCH models had different performances in different time frames. Kannadhasan et al. [14], Joshi [15], Banumathy et al. [16], Goudarzi and Ramanarayanan [17] found that the volatility of returns in Indian Stock Market was persistent, asymmetric and asymmetric negative effect was greater than the positive. Lin [18] examined the presence of heteroskedasticity and the leverage effect in the Chinese stock markets and found that the leverage effect was significant.

Husain and Uppal [19] while studying stock market volatility in Pakistan found GARCH (1, 1) to be the appropriate representation of conditional variance and also found an evidence of persistence in variance in returns. Hameed et al. [20], Mahreen and Nawazish [21] did modeling of conditional volatility of stock returns of the KSE-100 and found stock return volatility displays clustering and asymmetries. Mahmud and Mirza [22] used ARCH-type models in the Karachi Stock Exchange and concluded that the EGARCH (1, 1) captured the asymmetric effect efficiently during crisis. Waqar [23] confirmed that both EGARCH and TARCH models were best to capture the leverage (asymmetric) effect of KSE. Furthermore, Akhter and Khan [24] confirmed that daily, weekly and monthly KSE-100 Index return series showed non-normal distribution, stationarity and volatility clustering. They also found that EWMA model was appropriate to measure the volatility level in the monthly series, P-GARCH (1, 1) model in case of daily returns, while the GARCH (1, 1) model for weekly data. Javid and Mubarik [25] found that of all the asymmetric models used for KSE-100 Index, only EGARCH model had a negative leverage effect indicating that bad news decreased volatility and good news increased volatility. Authors also concluded that the asymmetric models were more appropriate in modeling the volatility of Pakistani market index.

All these studies provide evidence of volatility persistence and clustering to be present in the Pakistan Stock Exchange (PSX). In light of the above, it is important to empirically identify the volatility pattern of stock returns in Pakistan using the GARCH family of models. More specifically, the objectives of the present study are: (1) to estimate ARCH effects or conditional volatility of KSE 100 index of PSX market (2) to check the presence of asymmetric effects in PSX and what causes it to be more volatile (3) to establish which model is best in capturing asymmetric volatility in case of PSX and is there any difference in the variances predicted by different asymmetric models?

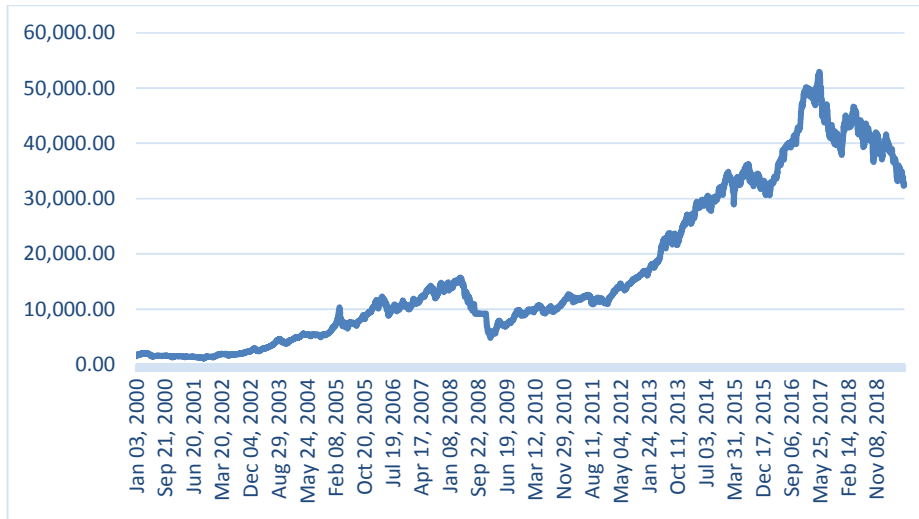
### **3 Trend Analysis of KSE 100 Index**

It is necessary to determine the time trend of the returns along with the growth pattern of these returns. Fig. 1 draws the daily return of KSE-100 index.

KSE-100 index, with a base of 1,000 points, started in November 1991. On July 25, 2019, the index stood at 32,366 points. Almost every index in the world routinely moves between bullish (increase) and bearish (decrease) trends, but for KSE-100 Index such trends have been more frequent and very intense. Looking at Fig. 1, the major portion of the bullish trend for KSE-100 Index has been witnessed after the crash of 2008. Initially a bullish trend started from 2003 and continued till the mighty fall of 2008. The main reasons behind the bullish trend 2003-2008 were US aid and ease of economic sanctions but overall all the economic indicators also showed a persistent increase. The most disastrous year (2008) in the history of financial markets in Pakistan dawned with index at 13,666, which climaxed at 15,654 by April 20<sup>th</sup>, 2008. Then the stock market came crashing down by 55% (lost 5,600 points) resulting in enforcement of floor fixed at 9,144 in August, lifting of which in December (after 108 days) resulted in another crash with index hurtling down

to 4782 points. This downfall was triggered by global financial crises and the new elected government in 2008.

Later on, KSE-100 index experienced recovery and reached 32,812 points at the end of 2015 despite the imposition of capital gains tax in July 2010. The key reasons behind this increase were Chinese investments in major sectors especially power generations and increase in foreign remittances. In January 2016, the three stock exchanges in Pakistan (Karachi Stock Exchange, Lahore Stock Exchange, and Islamabad Stock Exchange) were merged to establish a single stock exchange named the Pakistan Stock Exchange (PSX). As a result of this merger KSE 100 Index rose once again. In 2017 Pakistan qualified for the popular MSCI Emerging Markets Index in May 2017 and KSE-100 index reached an all-time high of 53127.24. Since then, KSE 100 index has once again decreased 5750 points or 15.13% since the beginning of 2019.



**Fig. 1. Daily closing prices of KSE-100 Index**

The conclusion drawn from this analysis of Fig. 1 is that there has been an abnormal increase in the index level without similar improvement in economic indicators and political and law and order situations. For example, from 2001-2019, the average GDP growth was 4.7 percent and average inflation rate was 8.24 percent but the rise of index in the same period has been spectacular.

#### 4 Data Description and Methodology

The aim of the study is to examine the volatility patterns exhibited by the daily stock returns in the PSX for 2000 to 2019 period. This sample period consists of 4831 daily observations for the 19 year trading period. Index chosen to capture the volatility displayed by the market is KSE-100 Index which is a capitalization weighted index of the shares of 100 leading companies in the Pakistan Stock Exchange and is a leading indicator of the Pakistan’s equity market. The data has been taken from the site of [www.investing.com](http://www.investing.com) and stata 14 has been used for analysis. All the GARCH models are measured through Gaussian error distribution. The daily return series of KSE-100 index has been generated as follows:

$$R_t = 100 * \log \left( \frac{P_t}{P_{t-1}} \right) \tag{1}$$

$P_t$  is the current index closing price at time stand  $P_{t-1}$  is showing the index closing price of previous day at time t-1. A time series data analysis for Pakistan Stock Exchange is being conducted with the help of descriptive statistics and GARCH family of models.

## 4.1 Theoretical modelling

### 4.1.1 Symmetric models

In the symmetric models, the conditional variance only depends on the magnitude of shocks while asymmetric models are designed in a way that the shocks of the same magnitude, positive or negative, affect future volatility in different way.

#### 4.1.1.1 ARCH (Autoregressive conditional heteroscedasticity) model

ARCH model was introduced by Engle [3]. The  $q$ th-order linear ARCH ( $q$ ) model only captures volatility clustering and has the following form

$$\sigma_t^2 = \omega + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2 \quad (2)$$

$\omega \geq 0$  and  $\alpha_i \geq 0$

#### 4.1.1.2 GARCH model

In this generalized ARCH (GARCH) model proposed by Bollerslev [4], the conditional variance is a linear function of its own lags. The specification of the GARCH (1, 1) model is

$$\sigma_t^2 = \omega + \sum \alpha \varepsilon_{t-1}^2 + \sum \beta \sigma_{t-1}^2 \quad (3)$$

Where  $\omega > 0$  and  $\alpha \geq 0$  and  $\beta \geq 0$ ,  $\varepsilon_t = \sigma_t z_t$  where  $z_t$  is standardized residual returns i.e. *iid* random variable with zero mean and variance =1), and  $\sigma_t^2$  is conditional variance.  $\varepsilon_{t-1}^2$  is the ARCH term and  $\sigma_{t-1}^2$  is the GARCH term.

### 4.1.2 Asymmetric GARCH models

Inability of symmetric GARCH models to account for the leverage effects observed in stock returns led to development of asymmetric models that could deal with this phenomena. This paper uses EGARCH, GJR form of Threshold GARCH, and asymmetric Power Arch Model from asymmetric class of models.

#### 4.1.2.1 The exponential GARCH (EGARCH) model

This EGARCH model was introduced by Nelson [5] to explain the asymmetries in the relationship between return and volatility. EGARCH (1,1) has the following specification.

$$\text{Log } \sigma_t^2 = \omega + \alpha (|z_{t-1}| - E(|z_{t-1}|)) + \gamma z_{t-1} + \beta \log(\sigma_{t-1}^2) \quad (4)$$

where  $\gamma$  is the asymmetric response parameter or leverage parameter.

#### 4.1.2.2 GJR Form of Threshold GARCH Model

This model was developed by Glosten, Jagannathan & Runkle [6]. The GJR-GARCH (1,1) model is stated in the equation below.

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2 I(\varepsilon_{t-1} < 0) + \beta \sigma_{t-1}^2 \quad (5)$$

where  $I$  denotes the indicator function.

4.1.2.3 Asymmetric power arch (APARCH) model

The APARCH, or APGARCH, model was developed by Ding, Granger and Engle [7]. The APGARCH (p,q) model has the following form.

$$\sigma_t^\delta = \omega + \sum_{i=1}^q \alpha_i |\varepsilon_{t-i}| - \gamma_i \varepsilon_{t-i}^2 + \sum_{i=1}^p \beta_i \sigma_{t-i}^\delta \tag{6}$$

4.2 Data analysis and results

The estimation results are presented in the following steps. Firstly, in order to determine the basic characteristics of data, descriptive analysis technique is used. Then different GARCH family models are used to determine the nature and extent of volatility.

4.2.1 Descriptive analysis

In Table 1, it is shown that the mean value of daily stock returns is 0.027. The standard deviation is 0.5768. The returns are negatively skewed and distribution is leptokurtic.

Table 1. Descriptive statistics

Indicator	Mean	Std. Deviation	Variance	Skewness	Kurtosis
KSE- 100 Index	.0278801	.5767864	.3326825	-.2525604	6.761846

*The negative Skewness (Leptokurtic distribution) indicates that an investor may expect frequent small gains and few large losses*

Fig. 2 shows time varying variance and clustering. Returns are volatile as shown by Figs. 1 and 2 so traditional models with the assumption of homoscedasticity are no longer valid for correcting the volatility of KSE 100 index. Instead, ARCH and GARCH models may be suitable in this scenario since they are capable of dealing with heteroscedasticity and clustering in time series data.

4.2.2 Test for stationarity and heteroscedasticity

In order to check whether return series is stationary or not at levels, Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests are applied with the null hypothesis that the variable contains unit root against the alternative that the variable is stationary Table 2.

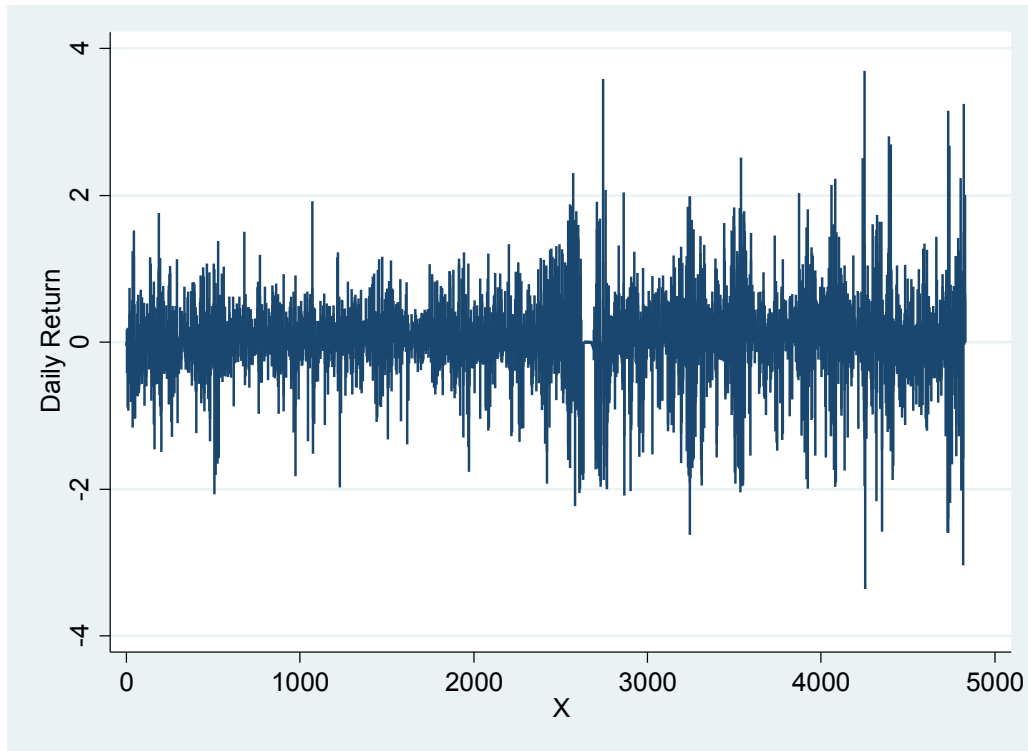
Table 2. Unit root analysis

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Augmented Dickey-Fuller (ADF)	Z(t) -62.248	-3.430	-2.860	-2.570
Phillips-Perron test (PP)	Z(rho) -4639.305	-20.700	-14.100	-11.300
	Z(t) -62.838	-3.430	-2.860	-2.570

*MacKinnon approximate p-value for Z(t) = 0.0000*

The results indicate that return series is stationary (confirmed by both ADF test and PP test). Hence the null hypothesis of non-stationarity is rejected. Next is the test for heteroscedasticity in the residuals of return series also known as ARCH effect.

There are numerous different approaches to check the ARCH effects. Two popular tests of autocorrelation in the squared residuals will be applied here. The two tests are the “Ljung- Box test” and “ARCH LM test.” Firstly, ARCH LM test is used to find out the existence of ARCH effects with the null hypothesis of no ARCH effects in the data series Table 3.



**Fig. 2. KSE 100 Index daily return**

**Table 3. ARCH LM test**

Lags	chi2	Df	Prob>chi2
1	546.410	1	0.0000

Probability of Chi square statistics showed significant results, which leads to the rejection of null hypothesis of no ARCH effects. The results verify the existence of ARCH effects in the KSE-100 index return series. Next the Ljung-Box test is also applied to determine whether autocorrelation is present in the series or not. To check this, Portmanteau test is applied. The results are presented in the Table 4.

**Table 4. Portmanteau test for white noise**

Portmanteau (Q) statistic	149.9748
Prob>chi2(10)	0.0000

*As the p-value is zero indicating significant autocorrelation. Both tests (ARCH LM and Ljung-Box) indicate that ARCH effects are present in the series*

#### 4.2.3 Symmetric ARCH/GARCH models

Next step is to estimate the ARCH model with the selected lag length based on AICs and BICs. It is shown in the Table 5 that the lag length is selected as 9 based on BICs value.

If sum of all the ARCH model coefficients is less than one, it means that the model is stationary. In the present scenario, the sum is equal to 0.87 hence confirming the stationarity of model.

**Table 5. Optimal lag length**

ARCH(p)	AIC	BIC	ARCH(p)	AIC	BIC
1	-36930.35	-36910.9	2	-37228.88	-37202.95
3	-37398.2	-37365.79	4	-37461.29	-37422.4
5	-37599.19	-37553.81	6	-37623.28	-37571.42
7	-37648.3	-37589.96	8	-37672.69	-37607.86
9	-37682.06	<b>-37610.75</b>	10	-37684.56	-37606.77
11	<b>-37688.12</b>	-37603.85	12	-37687.25	-37596.49

AIC and BIC provided conflicting results about the selection of optimal lag length. AIC shows lag length equal to 11 and BIC shows 9 lag length as optimal. Hence lag length of 9 (preferring parsimony) is selected. Next, ARCH (9) is tested and results are shown in Table 6

**Table 6. ARCH (9) test results**

	Coefficient	Std. Error	Z-statistics
Cons	.0623868	(0.003359)***	18.57
L1.	.25815	(.016017)***	16.12
L2	.147358	(.0171934)***	8.57
L3	.1040651	(.0148966)***	6.99
L4	.0270255	(.0132463)***	2.04
L5	.1236785	(.0149866)***	8.25
L6	.0567178	(.0111117)***	5.10
L7	.0578607	(.0126494)***	4.57
L8	.0635371	(.0099447)***	6.39
L9	.0341621	(.0080434)***	4.25

**4.2.4 GARCH model**

ARCH model used above captured many the features of KSE 100 index return series, but it has many lags in the variance equation (9). This problem of many lags was solved by Bollerslev [4] through generalization of the ARCH model, called GARCH (p, q) model. A GARCH model can mimic an ARCH model of infinite order. The results below in Table 9 summarize which lag lengths to use in GARCH (p, q) model based on their AICs and BICs. The AIC and BIC both selects a GARCH (2, 1) model (Table 7).

**Table 7. Optimal lag length**

GARCH(p q)	AIC	BIC
(1, 1)	6796.019	6821.95
(1, 2)	6792.207	6824.62
<b>(2, 1)</b>	<b>6790.769</b>	<b>6823.182</b>
(2, 2)	6792.388	6831.283

Finally the results of the estimated GARCH (2, 1) model is presented in Table 8.

The results indicate the statistical significance of all GARCH parameters. Also the estimated GARCH coefficient is considerably greater than the ARCH coefficients indicating that memory of market is longer than one period. Additionally it is more sensitive to its lagged values than to new shocks in market values. The sum of coefficients [(ARCH (1), ARCH (2), GARCH (1))] is 0.9749, implying highly persistent volatility.

As a standard post-estimation step, another Ljung-Box test is performed on the standardized squared residuals whose results are provided in Table 9.



**Table 8. GARCH (2, 1) test results**

<b>KSE-100 Index log returns</b>	<b>Coefficient</b>	<b>Z-statistics</b>
Constant	.0508729*** (.005422)	9.38
ARCH		
ARCH(1)	.2422854**** (.0179435)	13.50
ARCH(2)	-.06795*** (.018496)	-3.62
GARCH(1)	.8006199*** (.0128997)	62.07
Constant	.0111293*** (.0010456)	10.64

**Table 9. Portmanteau test for white noise**

Portmanteau (Q) statistic	31.2482
Prob> chi2(40)	0.8376

*The Ljung-Box Q test indicates that residuals have no significant left-over volatility clustering*

We also check if the GARCH (2, 1) is stationary or not. This is done through formal hypothesis testing and the results indicate that probability value of chi2 statistics shows significant results thus validating the stationarity of GARCH (2, 1) Table 10.

**Table 10. Stationarity check**

chi2( 1)	20.44
Prob> chi2	0.0000

#### 4.2.5 Asymmetric models

Next we discuss three asymmetric GARCH models to check which one captures the asymmetric response to new information better. As generally seen, volatility rises quickly and unexpectedly but it does not die out as fast as it rises. So there is an asymmetric response to volatility. The following models capture this asymmetric response in different ways Table 11.

**Table 11. Asymmetric models**

	<b>GJR_GARCH</b>	<b>EGARCH</b>	<b>APARCH</b>
<b>KSE 100 Index Returns</b>			
Cons	0.0616***(10.57)	0.0546***(10.95)	0.0609***(10.97)
ARCH	0.101***(10.62)	0.00283(0.21)	
GARCH	0.794***(78.34)		
TARCH	0.196***(10.49)		
EARCH		0.0944***(10.11)	
EARCH_A		0.353***(21.72)	
EGARCH		0.951***(182.51)	
APARCH			0.193***(19.50)
APARCH_E			0.277***(10.51)
PGARCH			0.810***(87.30)
Cons	0.00985***(10.35)	-0.0527***(-4.34)	0.0155***(7.55)
Power			1.436***(14.37)
N	4830	4830	4830

*t statistics in parentheses*

*\* p<0.05, \*\* p<0.01, \*\*\* p<0.001*

The EGARCH model strongly indicates leverage effect. The positive EARCH coefficient (0.094) implies that unanticipated improvement in price is more disturbing than anticipated improvement, but this effect is substantially less than the symmetric effect (0.353).

GJR TGARCH also captures the “leverage effect” of KSE 100 index returns series. Similar to the EGARCH model, we find that all ARCH, TARCH and GARCH terms are statistically significant. As the TARCH term is positive it means that positive shocks increase the volatility more than negative shocks.

APARCH model also shows strong asymmetry, with the large positive APARCH\_E coefficient (0.277) indicating that the response of market to unexpected increase in returns (good news) is much more volatile than the response to decreases in returns (bad news). The ARCH and GARCH terms also add up to one.

The three asymmetric models indicate that Pakistan Stock Exchange responds with more volatility to the unexpected good news but which model (among the three) be considered best and how? We once again turn to AIC BIC criterion Table 12.

**Table 12. AIC and BIC**

Model	Observations	AIC	BIC
GARCH(2 1)	4,830	7035.935	7061.866
GJR_GARCH	4,830	6708.615	6741.028
EGARCH	4,830	<b>6692.04</b>	<b>6730.936</b>
APARCH	4,830	6700.275	6739.171

Both AIC and BIC indicate that EGARCH model is best model for KSE 100 Index but it can be said that this model is slightly preferred over APARCH model. We also calculated correlations of variances calculated under different models (Table 13).

**Table 13. Correlation matrix of variances**

	GARCH(2, 1)	GJR_GARCH	EGARCH	APARCH
GARCH(2, 1)	1.0000			
GJR_GARCH	0.8724	1.0000		
EGARCH	0.8591	0.9879	1.0000	
APARCH	0.8870	0.9919	0.9895	1.0000

The correlation table of the predicted variances shows that the differences between the models are not great. The variances predicted by the asymmetric models are highly correlated, with the lowest correlation at almost 98%. All the asymmetric models are also highly correlated with GARCH (2,1) model. So all in all, any of the three asymmetric model could be used for KSE 100 index as their predicted variances are highly correlated (the lowest correlation being 98%).

Our results are consistent with those of Mehmud and Mirza [22], Waqar [23] who found EGARCH to be the best model for KSE 100 Index return series. Javid and Mubarik [25] however found out in their study that of all the asymmetric models used for KSE-100 Index, only EGARCH model had a negative leverage effect indicating that bad news decreased volatility and good news increased volatility. In our study all three asymmetric models showed that PSX was more volatile to good news as compared to bad news.

## 5 Conclusion

The purpose of the study is to study the volatility patterns displayed by the daily stock returns in the PSX for 2000 to 2019 period (4831 daily observations for the 19 year trading period) by using KSE-100 Index as a proxy for PSX. The volatility of the KSE 100 index returns have been modelled by using both symmetric and asymmetric GARCH models. The paper finds strong evidence that daily returns series is characterized by leptokurtic distribution and existence of conditional heteroscedasticity in the residuals series. The estimates of parameters of the GARCH (2, 1) model indicate a high degree of persistence in the volatility of stock returns on the PSX. Additionally the response to news arrival is asymmetrical. Arrival of good news

causes more volatility than the bad news. The three asymmetrical GARCH models (EGARCH, GJR-GARCH and APARCH) validate the presence of leverage effect in Pakistan Stock Exchange. AIC/BIC criterion pick EGARCH as best model but the analysis of correlations predicted by the three asymmetrical models shows that variances are highly correlated, thus ruling out any one asymmetrical model as a clear winner.

## Competing Interests

Authors have declared that no competing interests exist.

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