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Dynamic Volatility in Stock Market Returns: An Evidence from Islamic Index and Kse100 Index of Pakistan

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Abstract
This paper examines the time-varying volatility in the stock returns at Pakistan Stock Exchange (PSX). Time series data was used to gauge the volatility in the stock returns trough time series analysis techniques including the ADF, ARCH and GARCH family modeling for this purpose. The volatility concept is much familiar in the stock market analysis especially in the future decision making process by the investor. To further investigate this phenomenon, an Islamic index and KSE100 index at PSX were chosen with daily data ranging from June, 2009 to august 2020 with the total daily observations of 2772. The data was collected from investing.com. The ADF and Phillips-Perron (PP) unit root tests were performed to check the stationary of the series, where it was confirmed that the stock return of the KMI30 index as well as KSE100 index were no unit root at 1(0). The ARCH LM lest confirmed the ARCH effects in the KMI30 and kSE100 indices. The GARCH family modeling including GARCH (1,1), Mean GARCH (1,1), EGARCH (1,1), and TGARCH (1,1) were used. The results revealed that stock returns of the Islamic index (KMI30) and KSE100 index at Pakistan Stock Exchange (PSX) have the feature of volatility clustering. It is also gauged that stock returns of KMI30 index and kSE100 index are more volatile to bad news than good news. The study further explored that holders of such stocks can diversify their investment in some other related stocks to get arbitrage opportunity.

Keywords: KMI30, ARCH, GARCH, EGARCH, TGARCH, and PARCH

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Introduction

Stock traders and financial analysts are much interested in the volatility of the stock return in the capital market. They employed different indicators to track volatility and to forecast most favorable exit or entry points for trading. Some important techniques employed to gauge level of volatility are CBOE, volatility index, the average true range, and Bollinger Bands. Volatility refers to the fluctuations or instable position due to some shocks. These shocks have direct linked with the stock market and the future investment in the stocks. Risk-averse investor always intends to get risk premium in the form of arbitrage opportunity by diversifying portfolio. The volatility can affect the prices of the stock and therefore investors are more interested in the stock returns as compared to the prices (Campbell, Lo, and MacKinlay, 1997).

The stock market dynamism exhibits the time varying spillovers over the period of time because of uncertain situations. It directly captures the position because of its asymmetric response to the good news and bad news. Pakistan stock market (PSX) is an emerging market. Three stock markets are operating in the country named as Islamabad stock exchange, Lahore stock exchange, and Pakistan stock exchange formally known as Karachi stock exchange. Different stocks of the listed companies are offered for trading. Pakistan stock exchange (PSX) holds different indices like kSE100 index, KSEAllshares index, KMI30 index, KMIAll share index, KSE30 index etc. In this study, two indices including KSE-100 index and KMI-30 index are selected as proxies for stock returns to gauge volatility affects in the stock returns.

Many researchers favored stock returns for analysis instead of stock prices. Campbell, Lo, and MacKinlay (1997) used returns and argued that it is complete and scale free summary of the investment opportunities. Moreover, the stock returns series avails more statistical properties such as stationary that is the prior assumption of time series analysis (Tsay RS, 2010). These attributes of the returns give preference over prices. Further, this fluctuation in the returns is considered one of the prominent determinants to manage the world economy.

In the current study the researcher has collected high frequency daily data of the stock returns of KMI30 index and KSE100 index at Pakistan Stock Exchange (PSX) for the time period ranging from 8 June, 2009 to 12 August, 2020. The reason behind the high frequency data was that it experiences very rapid changes as compared to low frequency data. The study employed Augmented Dickey Filler (ADF) and Phillips-Perron (PP) tests to check the stationary of data series. ARCH LM test has performed to find out the ARCH affects. Then ARCH and GARCH series models have used to gauge symmetrical and asymmetrical response of the stock returns of KMI30 index and KSE100 index to the subject of volatility. The study also used some diagnostic tests to check the stability of the model equation.

1.1 Objectives of the study

The current study holds the following objectives.

a. To check the ARCH affects in the stock returns of KSE100 index and KMI30 index

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b. To determine the asymmetric or leverage affects in the KSE100 index and KMI30 index.
c. To evaluate the best forecasting model that rightly assess the volatility clustering in the stock exchange.

The current study comprised of five chapters. Chapter 1 discusses the introduction and main objective of the study. Chapter 2 reveals the previous literature work while chapter 3 deals with the data collection and research techniques used in the study. Chapter 4 reveals a detailed discussion of the data analysis. And finally chapter 5 gives conclusion.

2. Literature Review

The previous literature revealed that there are various types of research that employed ARCH and different GARCH series modeling to gauge the volatility in the stock market. These studies prolong over different time period and worked under different market structure.

Srinivasan (2011) used S&P 500 index at NYS exchange (US) as proxy for stock market returns. Different modeling of GARCH modeling series were employed to gauge the leverage affects. The study revealed that stock returns of the S&P 500 index are more exponentially volatile to the asymmetric information.

The study of Guidi (2009) used various asymmetric models to capture the volatility in the different world markets like in Germany, Swiss, and UK stock markets. The results confirmed the asymmetric affects in the stock returns.

Tse (1991) gauged the volatility in the stock return at the Tokyo stock exchange. He founded that stock returns series exhibited the ARCH and GARCH affects. The study also found non normality of the time series data.

Gokcan (2000) applied GARCH series to examine the symmetric and asymmetric response in the emerging market. The study exhibited that GARCH (1, 1) is the best one to examine the stock return' volatility behavior.

Lim and Sek (2013) checked the time varying volatility in the stock returns at the Malaysian stock market. They used all symmetric model ARCH and simple GARCH models as well as all asymmetric model including TGARCH, EGARCH and APARCH models to gauge the leverage affects on the stock returns. Their study founded that each GARCH model have different working performance in different times frames.

Similarly the work of Kannadhasan et al. (2018) Banumathy et al. (2012), and Goudarzi and Ramanarayanan (2009) argued that Indian stock returns hold volatility and there are leverage affects. The results revealed that Indian stock market have more asymmetric response to bad news as compared to good news.

Lin (2018) worked on the spillovers affects in the stock returns in china. He checked the existence of heteroscedasticity and leverage affects at the Chinese stock markets. The study founded that strong significant leverage affects were present in the stock markets of China.

Husain and Uppal (1999) applied GARCH (1, 1) model in order to diagnose the time varying volatility in the Pakistan stock markets. The study urged that GARCH (1, 1) is best to explain the

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asymmetrical position. They also argued that heteroscedasticity was present in the stock returns.

Hameed et al. (2006), performed the GARCH analysis to gauge the conditional volatility in the return of stocks using KSE-100 as proxy at Pakistan stock exchange. The results revealed that there were volatility clustering and asymmetries in the stock market.

Mahmud and Mirza (2011) used all GARCH series to capture the volatility phenomenon in the stock returns of KSE100 index at Karachi stock exchange. the study postulated that EGARCH (1, 1) was the best forecasting model based the selection criteria. They conclude that EGARCH model efficiently captured the asymmetric affects particularly t times of crises.

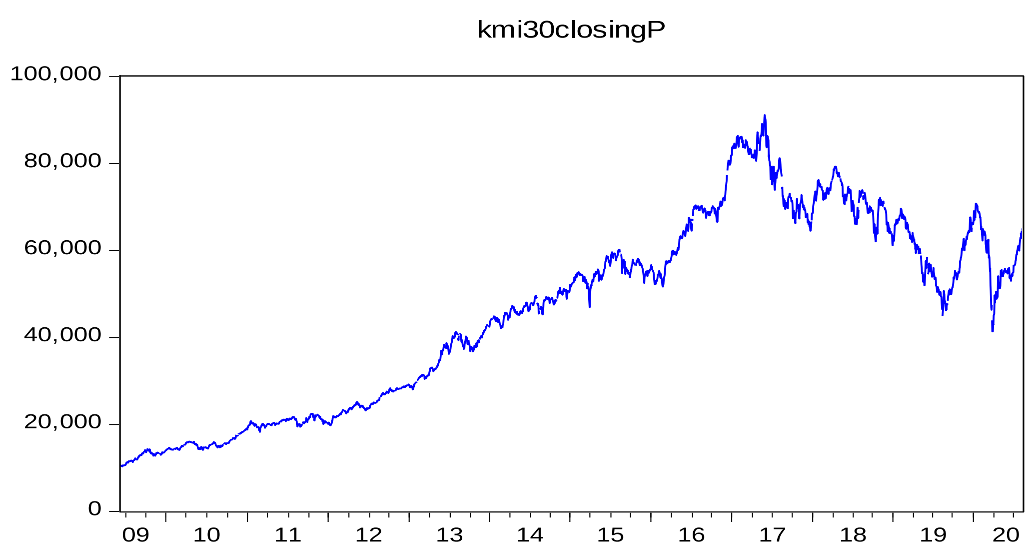
Similarly the work of Akhter and Khan (2016) used high frequency daily data, weekly data, and monthly data to capture the volatility in the KSE100 index. It was found that there were non normal series, stationary and volatility clustering in the stock returns. They used EWMA to determine the volatility in case of monthly data. They favored that PGARCH is an appropriate for daily data while GARCH (1, 1) is best forecasting in case of weekly data.

All these studies provide an evidence and proof that time varying volatility in the Pakistan stock market are exist and the stock returns have leverage affects due to bad news or good news.

Based on the previous literature, it is very indispensible to gauge the volatility behavior in the stock returns at Pakistan Stock exchange (PSX) by employing ARCH (p) model and all GARCH series models. For this purpose, the two stock indices including kSE-100 index and KMI-30 index were taken to perform all the GARCH series to capture the volatility in the stock returns.

2.1 The trends in the KSE 100 index and KMI-30 Index

It is very important to understand the trend pattern in the stock prices of KSE100 index and KMI30 at Pakistan stock exchange. This shows the volatility clustering in the data series before applying the ARCH and GARCH models to capturing the leverage affects. These trends of the KMI index and kSE100 are displaced by the following graphs.



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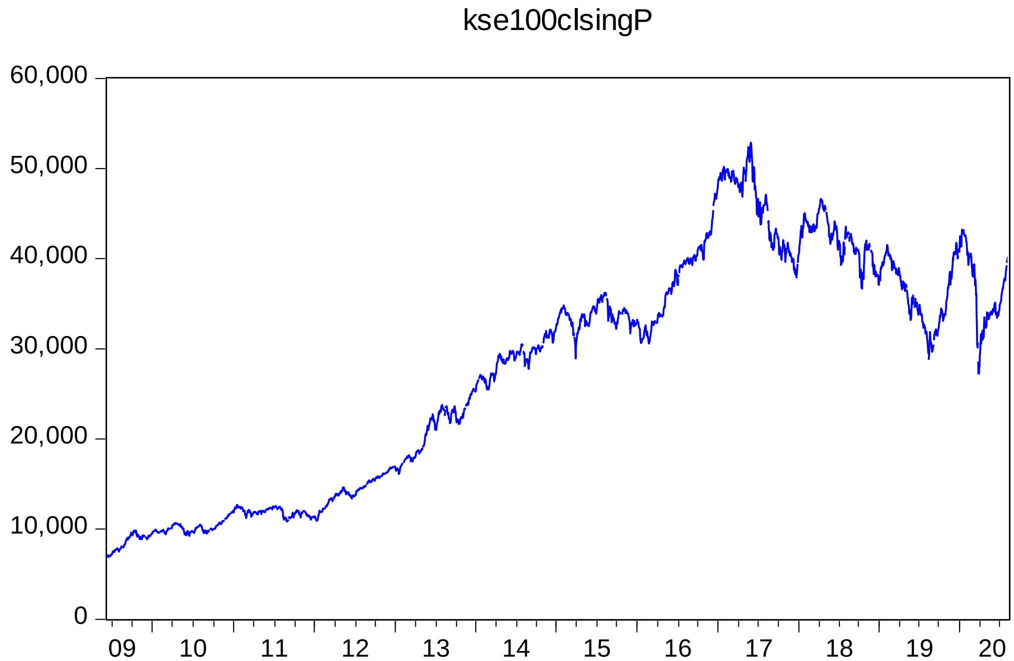

These graphs exhibits that there are regular increase in the stock prices of KMI30 index and KSE100 index. Although there are some fluctuations in the daily stock prices because of many asymmetrical affects. For example, in beginning of 2020 the stock prices are decreased up to a death point because of COVID-19 pandemic. Both stocks react to the bad news and good news.

3. Data description and Research Techniques

3.1 Data collection and variables construction.

The main aim of this study is to gauge the volatility clustering of the stock returns. For this purpose, Karachi Meezan Islamic index, abbreviated as KMI-30 index and KSE-100 index at Pakistan Stock Exchange were chosen as stock return series. The daily stock prices from 8 June 2009 to 12 August 2020 with total of 2772 observations were extracted from the investing.com. The stock returns were computed by $\ln(P_t / P_{t-1})$, where P_t is the current day closing price at time t period and P_{t-1} is the previous day closing price at time t-1 period. The KMI-30 index comprised of top 30 companies which have been evaluated for the Islamic Sharia criteria. The index is primarily based on the capitalization weighted index method.

3.2 Time Series analysis

Time series analysis was performed by various ARCH and GARCH family models to capture the time-varying volatility in the stock returns of KMI-30 index as well as KSE-100 index at Pakistan Stock Exchange (PSX). The ARCH is basically a symmetric model that fundamentally

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performed to estimate the conditional variance on the basis of scale of the shocks. While the others generalized form of ARCH models including GARCH, TGARCH, EGARCH well known as the GARCH family modeling, are the asymmetric models that further investigate that how and why these time-varying volatility can affect the future stock returns.

3.2.1 Autoregressive Conditional Heteroscedasticity (ARCH)

The ARCH was first used by Engle (1982) to estimate the variance. The ARCH model has two equations of mean equation and variance equation. The basic ARCH (1) model can be developed as $\boldsymbol{\sigma^2_t = b_0 + b_1 u^2_{t-1}}$**, where** $\boldsymbol{b_0>0}$**, and** $\boldsymbol{0 \le b_1 < 1}$

The model expressed that h_t (error variance) is the function of constant term (b_0) and the lagged squared value of the error term (u^2_{t-1}).

It is confirmed that greater the shocks in the previous period of t-1, the more ARCH affects will observe in the variance equation and vice versa. The variance equation of the ARCH model must fulfill the following two conditions otherwise the model will be explosive. The first condition is that coefficient of the constant term in the variance equation must be greater than 0 ($b_0 > 0$) and second one is that the coefficient of the squared error term in t-1 periods must be in between 0 and 1 i.e $0 > b_1 > 1$.

3.1.1 Preliminary testing for ARCH Model

3.1.1.a Data series at Stationary

The basic ARCH model is based on the assumption that data series must fulfill the condition of stationary that is series has no unit root. For this purpose, the ADF and Phillips-Perron (PP) unit root tests have performed.

3.1.1.b ARCH effects

The ARCH model is only performed in the case when there exist of ARCH effects. In order to meet this condition, we performed the ARCH LM test that exhibited the ARCH effects in the equation. The LM test assumes the Null hypothesis of having no arch effects (Homoskedasticity) and alternate hypothesis that describes the arch effects.

3.2.1 GARCH modeling

The GARCH is the generalized form of ARCH model. Tim Bollerslev developed the basic GARCH (1, 1) model in 1986 with following functional form i.e.

GARCH (1, 1) $\boldsymbol{\sigma^2_t = \omega + \alpha_0 \mu^2_{t-1} + b_1 \sigma^2_{t-1}}$**, where** $\boldsymbol{\omega > 0}$**,** $\boldsymbol{\alpha \ge 0}$**, and** $\boldsymbol{b_1 \ge 0}$**.**

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3.2.2 Asymmetric GARCH Models or GARCH series

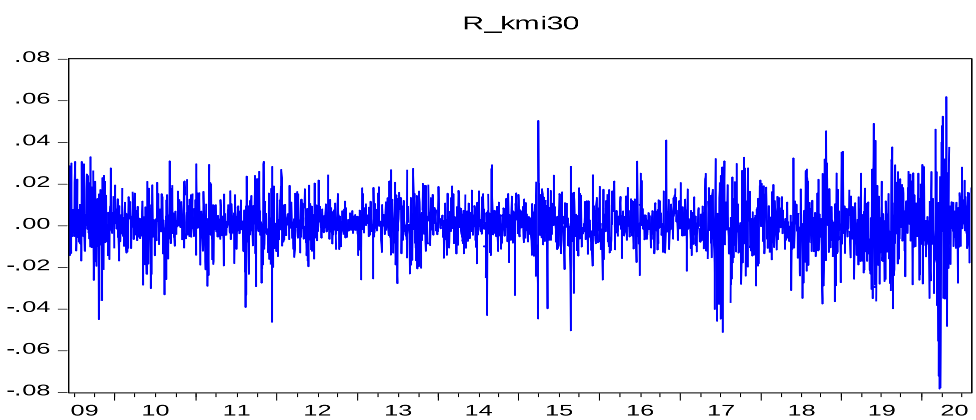
There are some asymmetric GARCH models that best forecast the volatility in the stock returns that are developed due to some bad or good news. These are GARCH family models. Based on the AIC and SIC criteria, the best GARCH model is selected to capture the time-varying volatility in the stock returns. These will be discussed in the upcoming analysis section as well. We used GARCH-Mean, TGARCH, and EGARCH modeling in this study to gauge the volatility clustering in the stock returns of the Islamic index of KMI-30 and KSE100 index at Pakistan Stock Exchange (PSX). The different GARCH models are summarized in the following table.

4. Data Analysis and Results

Before ARCH and GARCH analysis, some preliminary tests have been performed to determine the unique features of the data that are required for the basics of ARCH/GARCH modeling. For example, the volatility clustering of the series, flat tail, descriptive statistics, stationary of series and heteroscedasticity for ARCH effects has been checked. The results are each test are summarized as follow,

4.1 Volatility Clustering

The graphical presentation of the volatility clustering in the stock returns may lead to the evidence for the existence of the ARCH effects. The high volatility can either lead high losses or greater profit. The volatility of the daily stock returns of the KMI-30 index and KSE-100 index at Pakistan Stock Exchange are shown by the following graphs as under.



R_kmi30 series depicts volatility effects during the sample period. The volatility in the stock market has great impacts on the stock returns as it is shown by the graph. During the sample period from Dec 2019 to July, 2020, the volatility effects are greater due to the COVID-19 Pandemic. But later the market became stable and the return has adjusted this spillovers in the future period.

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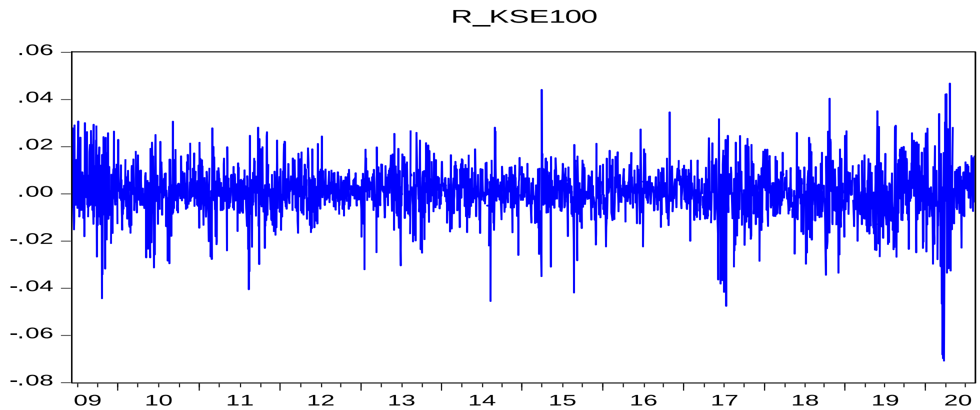

Similarly in case of KSE-100, the volatility is exhibited by the above graph. The stock return of the KSE-100 index at PSX is more responded to the volatility spillovers which are caused by bad news and good news during the early 2020 because of the COVID-19 pandemic. This volatility clustering exhibited that the return series of KMI-30 and KSE100 in the Pakistan Stock exchange (PSX) have ARCH effects.

4.2 Descriptive Statistics

Stock return	Mean	Median	Standard Dev;	Skewness	Kurtosis
R_KSE100	0.000639	0.000736	0.010495	-0.538564	7.010677
R_KMI30	0.000662	0.000420	0.011895	-0.404852	7.070554

The descriptive statistics showed that both stocks are skewed to the left side as the coefficients of the r_KMI30 and r_KSE100 are negative value. This negative skewness or Leptokurtic distribution determines that investors will gain less as compared to loss. These statistics postulated that stocks indices are more volatile to bad news as compared to good news.

4.3 Unit root test for stationary

Two tests are performed to examine the stationary of data. The Augmented Dickey-Fuller i.e. ADF test and Phillips-Perron (PP) tests are run to check that return series of KMI30 and kSE100 are stationary at level or not. The test results are summarized in the table.

	R_KMI30 Test statistics	R_KSE100 Test statistics
Augmented Dicky-Fuller AFD	-47.36941***	-46.22232***
Phillips-Perron (PP)	-47.43565***	-46.63466***

Note: The test critical Value at 1%, 5%, and 10% are -3.432518, -2.862384, and -2.567264 respectively.

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The table showed that return series of KMI30 and KSE100 are stationary at level as it is confirmed by both tests. Hence the null hypothesis that says that series has unit root is rejected. In both cases, the test statistics have larger value than test critical value.

4.4 Check for heteroscedasticity (ARCH effects)

It is utmost necessary to check the ARCH effect prior to run ARCH model for volatility purposes. Different methods are adopted for this purpose. Here the ARCH LM test is used to find out the heteroscedasticity in the conditional variance of the residuals. The Null hypothesis assumed that there is no arch effect mean no heteroscedasticity and the alternate hypothesis confirms the arch effects. The tests results are summarized in the table.

Table: ARCH LM tests

Stocks return	Chi 2	Df	Prob>Chi2
KMI-30	83.59195	1	0.0000
KSE-100	58.58905	1	0.0000

The results of the ARCH LM test showed that there is exist of ARCH effects in the return series of KMI30 and KSE100 at Pakistan stock exchange. Hence the null hypothesis is rejected and al alternate one is accepted.

4.5 ARCH model (symmetric model)

Since ARCH LM test confirmed that ARCH effects are existed. So next ARCH model is performed to estimates the ARCH parameters in order to capture the volatility in the stock returns of KMI-30 and KSE-100. The estimates are based on the basic ARCH (1) model. The tests results are summarized in the table.

TABLE: ARCH (1) model-estimates i.e. $\sigma^2_t = b_0 + b_1 u^2_{t-1}$, where $b_0>0$, and $0 \leq b_1 < 1$

Parameters	R_KMI30 (equ:1)	R_KSE100 (equ:2)
β_0	0.000103***	8.22E-05***
	(43.71002)	(42.66128)
β_1	0.293875***	0.269276***
	(14.02695)	(13.43218)
R^2	0.008427	0.012517
DW	2.078710	2.122237

Note: The z statistics values are reported in Parenthesis in both equations.

The above parameters estimates the variance equation of the ARCH (1) model. In ARCH model equation1, the coefficient of β_0 is 0.000103 (0.001%) which is greater than 0 and the coefficient

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of $\boldsymbol{\beta_1}$ is 0.293875 (29%) that holds $0 \leq b_1 < 1$. The positive coefficients determine the positive variance and hold the condition of best fitted ARCH model. If this is not the case, then the ARCH model will be explosive (instable results). More over both coefficients are significant at 5% as Z statistics in parenthesis are greater than the t critical value of 1.94. The model describes that return series of KMI-30 captures time-varying volatility as the coefficient of $\boldsymbol{\beta_1}$ is positive and significant at 5%, confirming that big shocks in the lagged value of the previous error term will bring a big volatility in the future variance of stock return of KMI30.

Similarly in ARCH model equation2, the coefficients of $\boldsymbol{\beta_0}$ and $\boldsymbol{\beta_1}$ holds the basics conditions of ARCH (1) model i.e. $b_0>0$, and $0 \leq b_1 < 1$. The coefficients are $\boldsymbol{\beta_0}$ (8.22E-05) and $\boldsymbol{\beta_1}$ (0.269276) are significant at 5% since z statistics are greater that 1.94 (T critical value). From the ARCH model equation 2, we concluded that time varying volatility can be found in the stock returns of KSE-100 at Pakistan Stock Exchange (PSX).

4.6 GARCH (p, q)

The GARCH (p, q) is the generalized form of ARCH (p) model. The simple GARCH is the extension of the ARCH model to the lagged period of the variance term. The simple GARCH (p, q) model is performed to capture the volatility in the returns of the KMI30 and KSE100 at Pakistan stock exchange PSX. The results of the variance equations of the GARCH (p, q) model are summarized in the table as under.

Table: GARCH (p, q) model i.e. $\sigma^2_t = \omega + \alpha_0\mu^2_{t-1} + \beta_1\sigma^2_{t-1}$, where $\omega>0$, $0<\beta_1<1$, $0<\alpha_0<0$, and $b_1 + \alpha_0 <$

1.

Parameters	R_KMI30 (equ:1)	R_KSE100 (equ:2)
ω	5.76E-06***	4.73E-06***
	(7.330869)	(7.092879)
$\boldsymbol{\alpha_0}$	0.129212***	0.136061***
	(11.09072)	(11.57588)
$\boldsymbol{\beta_1}$	0.830332***	0.822865***
	61.50717	(61.18729)
$\mathbf{R^2}$	0.008372	0.013007
DW	2.040378	2.070216

The above table contains two variance equations comprising of equ;1 and equ;2. As per equ:1 where GARCH (p, q) model is applied to estimate the spillover effect in the KMI30 stock returns. All the coefficients of the conditional variance specification fulfill the stability conditions. The ARCH coefficient ($\boldsymbol{\alpha_0}$=0.129212***) and the GARCH coefficient

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($\boldsymbol{\beta_1}$=0.830332***) are significant at 1% significance level, confirming that stock returns of KMI30 index are volatile in nature.

The GARCH equation:2 presents the variance equation of KSE100 index. The results proved that ARCH effects and GARCH effects are present since both coefficients meet the model stability specification criteria and significant at 1% significant level. This confirms that time varying volatility are present in the return of the stocks of the KSE-100 index.

4.7 The GARCH-M model

Simple GARCH model is not able to capture all aspects of volatility associated with the stock returns. In certain conditions, where investors are risk-averse and holds the position to capture the risk premium, then GARCH-mean model is performed on the basis of conditional mean that depend on its conditional variance. Simply when GARCH component is included in the mean equation, then we are actually developing a GARCH-Mean model. Basically the GARCH-Mean model estimates the time varying risk premium to explain the return of the stock. The following table contains the results of the GARCH-Mean (p, q) model for the stock returns of KMI-30 and KSE-100 indices at Pakistan Stock exchange for the sample period.

Table: GARCH-MEAN Model (based on Variance)

Mean Equation	**GARCH-Mean for R_KSE100**		**Mean Equation**	**GARCH-Mean for R_KMI30**	
Variable	**Coefficient**	**z-Statistic**	**Variable**	**Coefficient**	**z-Statistic**
GARCH	3.854541	1.133793	GARCH	3.836853	1.336199
C	0.000710	2.227861	C	0.000696	2.032770
R_KSE100(-1)	0.166911	7.845751	R_KMI30(-1)	0.131842	6.201118
Variance Equation.			**Variance Equation.**		
Variable	**Coefficient**	**z-Statistic**	**Variable**	**Coefficient**	**z-Statistic**
C	4.77E-06	7.116354	C	5.85E-06	7.346789
RESID(-1)^2	0.136145	11.54011	RESID(-1)^2	0.129767	11.04243
GARCH(-1)	0.822276	60.92384	GARCH(-1)	0.829043	60.50193
R-squared	0.010569		R-squared	0.005717	
Durbin-Watson stat	2.056289		Durbin-Watson stat	2.025588	

The GARCH portion in the mean equations for both indices states that mean-GARCH model is not capturing the risk premium volatility for the stock returns under KMI30 and KSE100 indices because the coefficients of mean GARCH are not significant at 1% level since z statistics value is less than the t critical value of 1.96. So it is recommended for the risk-averse investors to avoid

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mean-GARCH model as it is not far better than simple GARCH model to explain this phenomena.

4.8 TGARCH model or GJR model

Zakoian (1994) used TGARCH model or Threshold GARCH model as asymmetrical model to explain that how to perform asymmetric response to volatility that may caused due to various good news or bad news or some incidents or events like covid-19?. To perform TGARCH model, we just add multiplicative dummy variables to the variance equation in order to capture the shocks of good news or bad news.

The main equation of the TGARCH or GJR model is as under:

TGARCH/GJR model $\mathbf{h_t = \varphi + \theta_1 h_{t-1} + b_1 u^2_{t-1} + \gamma\, u^2_{t-1} D_{t-1},}$ **where**
Where D_t is used for dummy variable that takes either 1 for bad news or 0 for good news. $\boldsymbol{\gamma}$ is asymmetry or leverage term which always greater than 1 otherwise it is just simple GARCH model. Hence no need to use TGARCH model in that case. The results are summarized in the following table.

Table: TGARCH model

Parameters	**R_KMI30 (equ:1)**	**R_KSE100 (equ:2)**
φ	6.40E-06***	5.14E-06***
	(8.473101)	(7.997357)
$\boldsymbol{\theta_1}$	0.018614	0.022538**
	(1.811198)	(2.084122)
$\boldsymbol{\gamma}$	0.220157***	0.228125***
	(10.04274)	(9.952156)
$\mathbf{b_1}$	0.827648***	0.818668***
	(59.27099)	(57.23814)
$\mathbf{R^2}$	0.008511	0.012705
D-W	2.082500	2.119197

Note: z statistics are reported in parenthesis ()., * 1%, and ** 5% significance level**
The coefficient of asymmetric or leverage term (γ) is 22% for the KMI-30 index that explaining the difference between the good news and bad news subject to the volatility in the stock returns of the KMI-30 index. The TGARCH model is better explaining this phenomenon (asymmetric response to volatility) because the coefficient is significant at 1% level as z statistics is greater than 1.96.
Similarly in equation:2 that explains the TGARCH model for KSE-100 index, the coefficient of asymmetric or leverage term (γ) is 23% that explains asymmetric response to bad news or good news. Moreover the TGARCH is significantly explaining the asymmetrical response of the stock

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returns of KSE-100 to the subject of the volatility that arise due to bad news or good news. The asymmetric term is significant at 1% as z statistics is greater than the t critical value.
So from TGARCH model, we concluded that in term of **γ**, the KMI30 index's stock returns are influenced by positive information shock and the KSE-100 index is also influenced by positive information shock.

4.8 EGARCH Model

The EGARCH model is also asymmetric model that exponentially explains the effects of good news or bad news. It explains the asymmetric response either in increasing trend or decreasing trend. The results of the EGARCH model are summarized in the following table.
Table: EGARCH model: LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + **C(5)*RESID(-1)/@SQRT(GARCH(-1))** + C(6)*LOG(GARCH(-1))

Parameters	R_KMI30 (equ:1)	R_KSE100 (equ:2)
C(3)= ω	-0.628261***	-0.700057***
	(-11.28120)	(-10.81725)
C(4)= ŋ	0.213842***	0.230539***
	(11.29821)	(11.65838)
C(5)= γ	-0.144083***	-0.150236***
	(-12.35895)	(-12.36855)
C(6)= β_1	0.949157***	0.944303***
	(176.9822)	(149.3272)
R^2	0.008967	0.013360
D-W	2.074393	2.110070

Note: Z statistics value are reported in parenthesis ().*** denotes 1% significance level.
In the model, we are solely interested in the coefficient of the **C(5)= γ,** because it explains the exponential term in the TGARCH model. From the table, we examined that coefficients of the **C(5)= γ** for KMI-30 and KSE-100 index are -0.144083*** and -0.150236*** respectively. The coefficients of exponential term for KMI-30 index and for the KSE-100 index are negative but significant at 1% as z statistics value is greater than the 1.96. So we concluded from the EGARCH model, that effects of bad news on the stocks return is larger than the effects of the good news under the KMI-30 and KSE-100 indices.

4.9 Evaluation of GARCH models

Based on the following statistics, we can select the best GARCH model to forecast the results.

GARCH MODELS	Lowest Showers' information criterion SIC	Root mean square error RMSE	Lowest mean absolute error LMAE	Lowest mean absolute percent error LMAPE	Highest Theil's inequality coefficient
	R-KMI-30				

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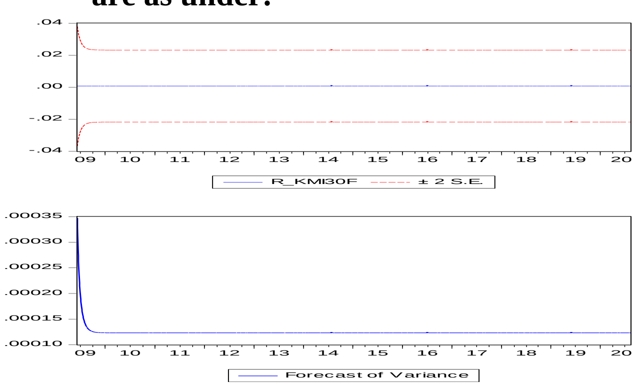
Simple GARCH (p, q)	-6.236638	0.011909	.008426	169.2128	.905426
Mean-GARCH (p, q)	-6.234445	.011919	.008444	182.1273	.892687
TGARCH	-6.274765	.011895	.008399	140.1590	.936783
EGARCH	**-6.280191**	**.011895**	**.008397**	**136.8212**	**.940829**
	R_KSE-100				
Simple GARCH (p, q)	-6.471477	.010511	.007477	190.1697	.895804
Mean-GARCH (p, q)	-6.469138	.010520	.007487	204.3938	.883601
TGARCH	-6.510339	.010496	.007463	154.6942	.928411
EGARCH	**-6.519225**	**.010495**	**.007463**	**149.6068**	**.933624**

Based on the above statistics, we observed that EGARCH or Exponential GARCH model is one of the best forecasting model because it met all specification criteria which are required for best forecasting model. So EGARCH is the best GARCH model to capture the asymmetric response to the new information prevailing in the stock market.

4.10 DYNAMIC FORECASTING OF EGARCH MODEL

We forecasted the results based on the EGARCH model. The main objective of the study is to gauge the time varying volatility in the returns of KMI-30 and kSE-100 indices. The exponential term can rightly assess this type of fluctuations in the stocks returns in the capital market that are caused by bad news or good news. The negative coefficient of the exponential term describes that bad news affects are larger than good news and vice versa.

1. **The dynamic forecasting results based on EGARCH for the stock return of KMI30 are as under:**



Forecast: R_KMI30F	
Actual: R_KMI30	
Forecast sample: 6/08/2009 8/12/2020	
Adjusted sample: 6/09/2009 8/12/2020	
Included observations: 2771	
Root Mean Squared Error	0.011895
Mean Absolute Error	0.008397
Mean Abs. Percent Error	136.8212
Theil Inequality Coefficient	0.940829
Bias Proportion	0.000033
Variance Proportion	0.999602
Covariance Proportion	0.000365

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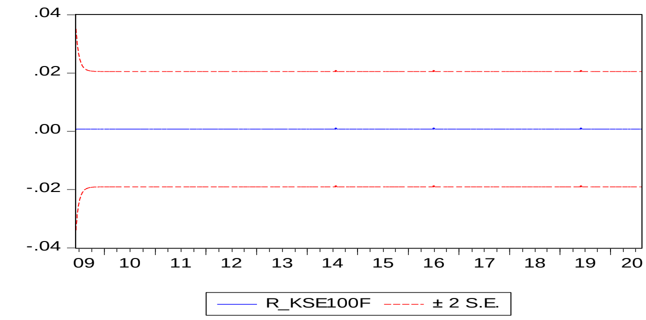
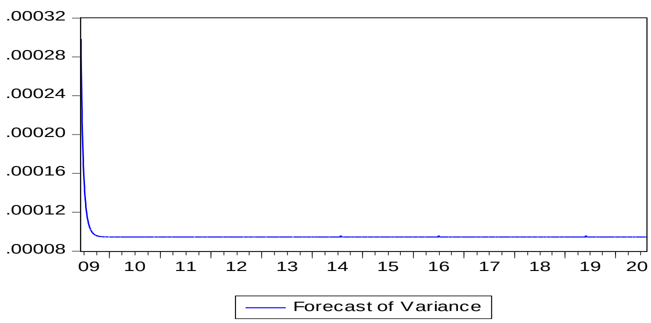
Based on the asymmetric model forecasting (EGARCH), the risk-averse investors are much devoted to the shocks spread by bad news and good news prior to hold the asset, because the chances of less error lead to less volatility or fluctuations in the stock returns. Investors hold those stocks which are less volatile in nature. The dynamic forecasting of EGARCH proved that volatility in the stock return of KMI-30 index is stable and within the standard error bands.

2. The dynamic forecasting results based on EGARCH for the stock return of KSE-100 are as under:



Forecast: R_KSE100F	
Actual: R_KSE100	
Forecast sample: 6/08/2009 8/12/2020	
Adjusted sample: 6/09/2009 8/12/2020	
Included observations: 2771	
Root Mean Squared Error	0.010495
Mean Absolute Error	0.007463
Mean Abs. Percent Error	149.6068
Theil Inequality Coefficient	0.933624
Bias Proportion	0.000071
Variance Proportion	0.999409
Covariance Proportion	0.000520



The dynamic forecasting by EGARCH for the stock return of KSE-100 displayed stable results, because asymmetric response to the volatility, and shocks from bad news and good news in respect of the KSE100 stock returns are within the standards error bands. It will guide the investor to hold the stock which is less volatile in nature. Based on the dynamic forecasting, one can predict better forecasting.

4.11 Diagnostic tests

4.11.1 ARCH LM test: H_0: homoskedasticity (p value greater than 1%), otherwise accept H_1.

Stocks return	Chi 2	Df	Prob>Chi2
KMI-30	0.000881	1	0.9763
KSE-100	0.155554	1	0.6933

The LM diagnostic test confirmed that p value of chi square Chi2 is greater than 1% significant level in both equations. Hence no heteroscedasticity is found.

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4.11.2 Correlogram Squared residuals tests

This test is performed to check the serial correlation in the residuals. The test results revealed that there is no serial correlation in the residuals because the p value of all 36 lags is greater than 1% of the significant level. The test results are given in Annexure..

5. CONCLUSION

The main purpose of this study is to gauge the time varying volatility associated with the stock returns. For this purpose, two different indices at Pakistan stock exchange were selected. The daily stock prices of KSE-100 index (a conventional index of top 100 companies) and KMI-30(Islamic index of Karachi Meezan Islamic top 30 companies) were taken for the period from 8 June, 2009 to 12 August, 2020 with total daily observations of 2772. The stock return was calculated on the basis of log return. The stock return series of KMI-30 and KSE-100 were examined for the time varying volatility by ARCH (p) model and all GARCH series including simple GARCH (p, q) model, Mean-GARCH model, TGARCH, and EGARCH.

The study founded that the daily stock return series of KMI-30 index and KSE-100 index at Pakistan stock exchange are stationary at level and have the characteristics of conditional heteroscedasticity in their residuals which lead to further analysis of ARCH and GARCH models. So the stock returns series have been modeled by ARCH (p) and all GARCH series to examine symmetric and asymmetric response to volatility in the stock return series of the KMI-30 index and KSE-100 index. The results proved that return series of both conventional index as well as Islamic index have the features of volatility. All the asymmetrical models including TGARCH and EGARCH confirmed the presence of leverage or volatility effects in the stock returns at Pakistan stock exchange. The study also revealed that EGARCH is the best forecasting asymmetrical model for future forecasting purposes. The study implemented EGARCH model for dynamic forecasting. EGARCH model gauged that asymmetric response of the stock returns series to bad news have lager affects than good news because of the negative coefficient of the exponential term. The diagnostic tests including ARCH LM tests and Correlogram squared residuals diagnostic test for serial correlation revealed that there is no presence of heteroscedasticity and serial correlation.

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