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Modeling Volatility In The Islamic Equity Market: A Case Of Pakistan

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Abstract

Return and risk walk off hand-in-hand. Many investors attempt to forecast the return associated with a potential future investment. But their ability to predict the volatility, or risk, involved with that return is no lessimperative. The study at hand is an endeavor to capture the variance in KSE Islamic All Share Index of Pakistan using the popular ARCH-GARCH modeling methods. Daily data of the Index were taken from November 2015 to June 2020 that led to 1117 observations.It was observed that KSE Islamic All Share Index did have ARCH effects implying that volatility in the Index was not stagnant at all throughout the period of study. In order to arrive at a more parsimonious model, the GARCH technique was also employed and significant results were drawn. Finally, the TGARCH model revealed asymmetries in the effect of negative and positive news on stock returns. It was found that negative or bad news had a deeper influence on the volatility of returns of the Index than positive or good news.

Keywords: ARCH, GARCH, TGARCH, Volatility, KSE Islamic All Share Index, Prediction

1. Introduction

Being an Islamic country, many of the investors in Pakistan prefer to invest in companies that are Shariah-compliant. In order to address this issue, the Steering Committee, made for the development of Islamic banking and finance in Pakistan, instituted a sub-committee for the development of Islamic Capital Market. The very first meeting of that committee was held on March 6, 2014 in which a proposal for developing an All Shares Islamic Index of the country was approved that would include all Shariah compliant companies listed on the Karachi Stock Exchange. One of the motivations for making a separate index for Islamic, or Shariah compliant, shares was to judge their performance and compare them with the conventional, or non Shariah compliant, shares. The current study is an attempt to see the performance of this rather newly created Islamic Index of the country.

An investor of shares normally looks into the return those shares are expected to offer him/her in the future. However, equally valuable, if not more, is the variability or unevenness expected in those returns. The current study is conducted to measure this volatility behavior in share returns of the Shariah compliant companies.

There are two closely related objectives of the study. The foremost is to know if there is a constant long-run variability in the returns of KSE Islamic All Shares Index. If it is found that the first

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objective does not hold true, or that the variability is not constant, the second objective, then, is to explore the number of autoregressive and/or moving average terms required to identify or explain the future volatility in the returns of these Islamic shares.

2. Review of Literature

There has been quite a bit of work in different countries on modeling the volatility of returns of stock indices. Srinivasan(2011), for instance, predicted stock market volatility of US stock returns of S&P 500 and noticed GARCH effects in the index. Danielson (1994) applied different models of ARCH on S&P 500 and noticed that EGARCH(2, 1) model gave better results than any ARCH, GARCH or IGARCH configuration. Similarly, TSE (1991) observed stock return variance of Tokyo Stock Exchange and found that ARCH and GARCH effects were there. Guidi (2009) observed the risk in returns UK, Swiss and German stock markets and concluded that there were significant ARCH effects in all stock markets in all of these countries.Another researcher named Gokean (2000) observed that compared with ARCH, the GARCH models forecast better in new and growing markets.

A few researchers in India namely Kannadhasan et al (2018), Joshi (2014), Banumathy et al (2012), and Goudarzi&Ramanarayanan (2009) computed the volatility of returns in the Indian stock market. These studies focused more on the TGARCH models and concluded that negative news were often more powerful in their influence than the positive news.

Lim and Sek (2013) observed that the variance of share market portrayed asymmetric and symmetric GARCH epitomesin Malaysia. Lin (2018) also demonstrated the variance of SSE composite index by employing the GARCH models and found that the index had GARCH effects.

Some researchers in Pakistan have conducted studies to explain variability clustering in stock market. To discuss a few, Akhter and Khan (2016) identifiedthat KSE-100 returns series depicteddistribution that was not normal, stationarity, andto some extentthe volatility clustering. Other scholarsalso observed that positive and negative news had a differenteffect on stock variance.(Javid&Mubarik, 2016).

Husain and Uppal (1999) also investigated the volatility of stock returns in Pakistan andobserved thatGARCH(1, 1) model was moresuitable for describing the conditional variance. Hameed et al (2006)foundthat modeling of the conditional variance of returns of Pakistani stocksdisclosedasymmetries and,to some extent, clustering. Mahmud and Mirza (2011)also employed ARCHmodels in Karachi Stock Exchange and revealed that the EGARCH(1, 1) capturedthe asymmetric effect pragmaticallyinthe times of financial crisis.

3. Research Methodology

As KSE Islamic All Share Index is a rather newly created Stock Index in Pakistan, the data is available only since November 18, 2015. Hence, the current study includes the data of the Index right from its inception, i.e., November 18, 2015 up until May 20, 2020. However, since most time series are trended and KSE Islamic All Share Index was no exception, the absolute values of the daily Index were converted into daily return figures in order to induce stationarity in the variable.

The ARCH family of models, first introduced by Engle (1982),was employed for modeling the volatility in stock returns.

As per the requirements of ARCH methodology, it was determined in the initial stage if ARCH effects were there in our time series of consideration or not. Then, after the variable was found to have high and low volatility periods, ARCH tests were employed in lower and higher orders. These were followed by other variations of the ARCH, namely the GARCH, GARCH-M, TGARCH, and EGARCH.

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Figures of KSE Islamic All Shares Index were taken on a daily basis from ksestocks.com from November 18, 2015 to May 20, 2020 that led to 1117 observations.

4. Analyses and Findings

Being a typical time series variable, the KSE Islamic All Share Index is also a non-stationary series and needs to be differencedfor achieving stationarity. One way of inducing stationarity is to compute the daily returns of the Index that is computed by dividing the difference between the previous and current value of the Index by its previous value. Hence, returns of the Index were computed and then a simple line graph was formed to check for ARCH effects in the time series. This graph is presented in figure 1:

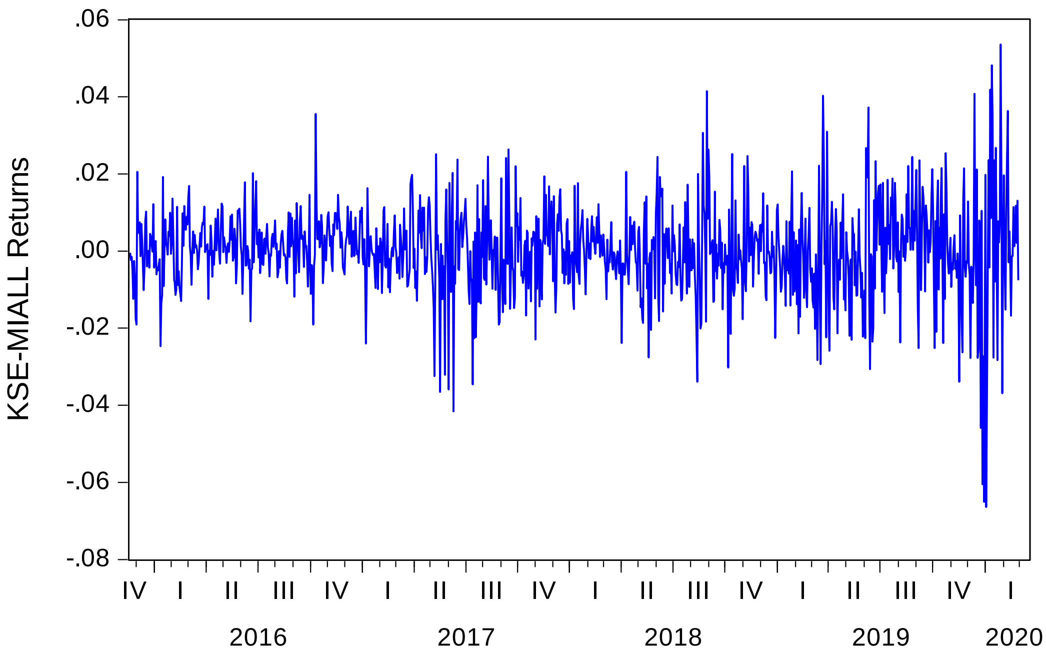

Figure 1: Plot of the Returns of KSE Islamic All Share Index

For the purpose of convenience, the KSE Islamic All Share Index is abbreviated as 'KSE-MIALL' in the analyses and findings section of the paper (the Index is abbreviated in the same manner by Pakistan Stock Exchange as well).

Figure 1 presents the volatility in our time series for the period covered showing clear evidence of non-constant volatility of returns or ARCH type effects during the period of study. This volatility is at its maximum during the last quarter of 2019 and the first quarter of the year 2020.In fact, the Indexgoes beyond the 20,000-point level during the very early days 2020 and then reaches its lowest point during March 2020 (slides below the 13,000-point level). Hence, to start the analysis, our variable is now subjected to AR(1) model. This analysis is done through EViews and the ordinary least squares method of regression is employed.

Table 1: An AR(1) Model for KSE Islamic All Share Index

Dependent Variable: KSE-MIALL Returns Method: Least Squares

Observations included: 1115 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	.0001	.0003	.318	.750
KSE-RETURNS(-1)	.155	.030	5.250	.000

We do not use the results taken from table 1 to deduce anything. This model has been run just to compute the residuals which are needed to measure ARCH effects. There can be ARCH effects at different lag levels; we, however, start with the most parsimonious one, i.e., the ARCH(1), the results of which are displayed in table 2:

Table 2: Testing for ARCH(1) Effects in the KSE Islamic All Share Index

Heteroskedasticity Test: ARCH			
F-statistic	13.278	Prob. F(1,1112)	.000
Obs*R-squared	13.145	Prob. Chi-Square(1)	.000

Dependent Variable: RESID^2
Method: Least Squares
Included observations: 1114 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	.0001	1.05E-05	11.372	.000
RESID^2(-1)	.109	.030	3.644	.000

The value of theObs*R-squared statistic, as depicted in table 2, has a value of 13.278 with a highly significant p valuedenoting that the null hypothesis ofnon-existence ofheteroskedasticity can be rejectedmeaning thatthere are ARCH(1) effects.We try with a higher level of ARCH effects as well before going with the ARCH model.

Table 3: Testing for ARCH(4) Effects in the KSE Islamic All Share Index

Heteroskedasticity Test: ARCH			
F-statistic	52.667	Prob. F(4,1106)	.000
Obs*R-squared	177.761	Prob. Chi-Square(4)	.000

Dependent Variable: RESID^2
Method: Least Squares
Included observations: 1111 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	5.78E-05	1.07E-05	5.380	.000
RESID^2(-1)	-.015	.030	-.494	.622
RESID^2(-2)	.269	.029	9.206	.000
RESID^2(-3)	.207	.029	7.079	.000

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RESID^2(-4)	.109	.030	3.657	.000

Table 3gives results ofARCH(4) effects. The model now has an even higher Observed R-squared value (177.76, $p < 0.0001$) and all, but one, lagsare highly significant. It is therefore possible that KSE-MIALL is characterized by ARCH(4) or some other higher order ARCH effects.
In the following table, we formally run an ARCH(1) model with ML ARCH estimation method.

Table 4: An ARCH(1) Model for the KSE Islamic All Share Index

Dependent Variable: KSE-MIALLRETURNS
Method: ML - ARCH (Marquardt) - Normal distribution
Included observations: 1115 after adjustments
Convergence achieved after 12 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	.0003	.0003	.921	.357
KSE-MIALLRETURNS(-1)	.189	.021	8.826	.000
Variance Equation				
C	9.79E-05	3.71E-06	26.361	.000
RESID(-1)^2	.322	.034	9.336	.000

Results of the ARCH(1) model displayed in table 4 reveal that the coefficient of ARCH(1), as represented by the "RESID(-1)^2" in the variance equation, is positive (.322) and highly significant ($p < 0.0001$). This is consistent with the findings we obtained from the ordinary least squares method.
To see the impact of a higher order ARCH model, we run ARCH(2), ARCH(3) and ARCH(4). We find that for all these ARCH models, the coefficients are statistically significant for all lags involved. The following table shows results of the ARCH(4) model.

Table 5: An ARCH(4) Model for the KSE Islamic All Share Index

Dependent Variable: KSE-MIALL RETURNS
Method: ML - ARCH (Marquardt) - Normal distribution
Included observations: 1115 after adjustments
Presample variance: backcast (parameter = .7)
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*RESID(-2)^2 + C(6)*RESID(-3)^2 + C(7)*RESID(-4)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	.0007	.0003	2.320	.020
KSE-MIALLRETURNS(-1)	.197	.030	6.484	.000

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Variance Equation				
C	4.96E-05	3.48E-06	14.267	.000
RESID(-1)^2	.119	.028	4.286	.000
RESID(-2)^2	.203	.039	5.231	.000
RESID(-3)^2	.203	.038	5.269	.000
RESID(-4)^2	.120	.027	4.433	.000

As stated earlier, all the coefficients in ARCH(4) model are significant and positive. We, however, notice that the coefficient of the first lag was negative and insignificant as per the OLS method.
Including the fifth lag in the ARCH model also makes the first lag slightly insignificant (p = .067) though positive.
It is often argued that ARCH(q) models have too many lags involved making them less parsimonious than their more advanced counterparts. Also, they resemble more with the moving average models. In order to sort this matter, we employ a GARCH(p,q) model to see whether we may come up with a simpler configuration. We will naturally have to start with GARCH(1,1).

Table 6: A GARCH(1,1) Model for the KSE Islamic All Share Index

Dependent Variable: KSE-MIALL RETURNS
Method: ML - ARCH (Marquardt) - Normal distribution
Included observations: 1115 after adjustments
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)
Presample variance: backcast (parameter = 0.7)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	.0007	.0003	2.443	.015
KSE-MIALLRETURNS(-1)	.203	.034	6.009	.000
Variance Equation				
C	3.14E-06	7.94E-07	3.947718	.0001
RESID(-1)^2	.121	.016	7.631	.000
GARCH(-1)	.858	.016	54.713	.000

The term "RESID(-1)^2" which represents ARCH(1) is positive with a coefficient of .12 and highly significant. The GARCH term has a much higher coefficient value of .858 which is highly significant as well. Hence, apart from the ARCH effects, there are reasonably irrepressible effects of the lagged conditional variance terms as well.
We check for higher orders of GARCH as well including GARCH(2, 2) having three insignificant parameters, GARCH(3, 3) having all parameters significant, GARCH(4, 4) having four insignificant parameters, GARCH(1, 4) having one insignificant parameter, and GARCH(2, 4) having four insignificant parameters. We, however, display the results of GARCH(3, 3) only since it has all its parameters statistically significant. The results are given in table 7.

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Table 7: A GARCH(3,3) Model for the KSE Islamic All Share Index

Dependent Variable: KSE-MIALLRETURNS
Method: ML - ARCH (Marquardt) - Normal distribution
Included observations: 1115 after adjustments
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*RESID(-2)^2 + C(6)*RESID(-3)^2 + C(7)*GARCH(-1) + C(8)*GARCH(-2) + C(9)*GARCH(-3)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	.0007	.0003	2.532	.011
KSE-MIALLRETURNS(-1)	.198	.032	6.088	.000
Variance Equation				
C	1.10E-05	2.67E-06	4.112	.000
RESID(-1)^2	.118	.025	4.344	.000
RESID(-2)^2	.198	.032	6.192	.000
RESID(-3)^2	.159	.023	7.012	.000
GARCH(-1)	-.728	.049	-14.701	.000
GARCH(-2)	.463	.038	12.031	.000
GARCH(-3)	.732	.041	17.809	.000

We finally employ another variant of GARCH known as the TGARCH, or the Threshold GARCH which was derived from the works ofGlostenet al. (1993) and Zakoian (1994). In fact, the ARCH and GARCH models we have used so far are all symmetric because the residual term is squared. Hence, the magnitude, and not the sign, of the relationship is what matters in ARCH and GARCH models. This entails that as per these models, a positive shock and a negative shock will have the same effect on the volatility of stock returns. In actuality, however, it has been seen that negative shocks have a more profound effect on stock return volatility than positive ones.

In order to capture for these asymmetries in terms of the effect of positive and negative shocks, the TGARCH model may be employed that adds a multiplicative dummy in the variance equation to understand the disparitybetween the impact of positive and negative shocks.

Table 8: A TGARCH(1,1) Model for the KSE Islamic All Share Index

Dependent Variable: KSE-MIALLRETURNS
Method: ML - ARCH (Marquardt) - Normal distribution
Included observations: 1115 after adjustments
Presample variance: backcast (parameter = .7)
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*RESID(-1)^2*(RESID(-1)<0) +C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000196	0.000276	0.711474	0.4768
KSE_MIALL_RETURNS(-1)	0.226269	0.031993	7.072380	0.0000

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Variance Equation				
C	3.68E-06	7.51E-07	4.894545	0.0000
RESID(-1)^2	0.008330	0.013282	0.627224	0.5305
RESID(-1)^2*(RESID(-1)<0)	0.215870	0.033443	6.454958	0.0000
GARCH(-1)	0.858494	0.017848	48.10012	0.0000

Table 8 offers the results of TGARCH(1, 1) model. It is evident that the coefficient of the "RESID(-1)^2*(RESID(-1)<0)" term in the variance equation is positive and significant at one percent level.Hence, we may conclude that for KSE Islamic All Share Index, asymmetries are there in the nature of the news in such a manner that bad news affect the volatility of the returns more than the good news.

5. Conclusion

The current study employed the ARCH family of modeling techniques to model the volatility of KSE Islamic All Share Index. It was explored that the series did show a non-constant variance during the period of study demonstrating the existence of ARCH effects. It was also found that the ARCH(1) model was more parsimonious and was better than the higher order ARCH models. The GARCH modeling was also used and it was found that volatility in the returns could better be modelled by either GARCH(1,1) --- the simplest GARCH configuration, or GARCH(3,3) --- a rather over-parameterized approach. Finally the TGARCH method revealed that investors in KSE-MIALL did not treat negative and positive news equally. Hence, the index was more volatile for bad news than what it was for the good news.

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