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Stock Index Prediction Using the Variance Modeling Approach

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A B S T R A C T

The importance of stock index forecasting can never be underestimated in the world of investments. However, for a rational investor who is reasonably risk-averse, the ability to forecast volatility in the index is at least as important, if not more, as the capability to predict the return. The current study measured the volatility in the KSE 100 Index using the ARCH-GARCH modeling techniques. Daily figures of the Index were taken from January 2010 to August 2020 leading to 2,660 observations. It was found that KSE 100 Index was characterized by ARCH effects meaning that there were certain periods that were more volatile followed by relatively tranquil periods. In operational terms, the ARCH(4) configuration delivered better results than ARCH(1) or any other ARCH model. The best GARCH model, on the other hand, for the KSE 100 Index was found to be GARCH(1,1). Finally, analysis of the TGARCH and the EGARCH portrayed that asymmetries were there in the positive and negative news for the KSE 100 Index. Hence, bad news was found to have a significantly larger impact on the volatility of the Index than good news.

INTRODUCTION

For a modern-day investor planning to buy a share of common stock, a forecast of the rate of return the stock offers is not enough. He or she will also be interested in knowing the expected variability (or volatility) of returns in the stock. An obvious reason is that most of the investors are risk-averse, and therefore, will prefer to invest in a less risky stock to a riskier one.

The present study attempts to measure the volatility of stock returns. However, instead of measuring the variance of individual stocks, it endeavors to measure, and compare, the volatility of KSE 100 Index which represents movements in the stock market in Pakistan as a whole. The study will, therefore, be employing the popular *ARCH* family of modeling techniques first presented by Engle (1982) and which

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is based on the premise that variance of the error term at any given time is dependent on the squared error from previous periods.

The study holds two objectives: One is to explore whether the level of volatility in KSE 100 Index is constant in the long-run or not. If the answer to the first objective is in negation, or in other words, if it is found that there are periods of higher volatility followed by lower volatility or vice versa in the index, then the other objective of the study is to find how many autoregressive and/or moving average terms of variance are required to explain the current, or future, variance in the returns of the index.

REVIEW OF LITERATURE

Up so far, many researches in different countries have used the ARCH family of models to apprehend the variance in returns of stock markets. Studies have shown that markets at embryonic stage have their own operational scopes. Developing markets face many failures including asymmetric information, monitored frameworks, shallow markets, and projected swapping of small investors along with many more.

Stock market volatility was forecasted in US stock returns of S&P 500 index, and GARCH effects were noticed (Srinivasan, 2011). In a study specifically conducted to compare the effects of different configurations of the ARCH family of models, Danielson (1994) brought into being that compared with the GARCH(*1*, *2*), ARCH(*5*), and IGARCH(*1*, *1*, *0*) models, EGARCH(*2*, *1*) model executed better results on S&P 500 Index's daily data taken from 1980 to 1987. Volatility at the Tokyo Stock Exchange in stock returns was observed by Tse (1991) who found significant effects of GARCH and ARCH returns. Another researcher Guidi (2009) studied the volatility of Swiss, German and UK stock market indices and found significant GARCH effects in all of them.

Gokean (2000) in his study found that GARCH(*1*, *1*) model predicted volatility better in evolving stock markets. The variability of returns in stock market in India was established by Kannadhasan et al (2018), Joshi (2014), Banumathy et al (2012), and Goudarzi & Ramanarayanan (2009). These studies showed that the insistent asymmetric negative outcome was often larger than the positive one. Lim and Sek (2013) found that the volatility of stock market showed symmetric and asymmetric GARCH archetypes in Malaysia. Lin (2018) also modeled the volatility of SSE composite index using the GARCH models and concluded that the index did have GARCH effects.

There have been a few studies conducted in Pakistan to explore volatility clustering in its stock market. For instance, Akhter and Khan (2016) established that KSE-100 Index returns series on daily, weekly, and monthly basis portrayed distribution that was non-normal, stationarity, and also volatility clustering.

Also, they stated that the new EWMA model worked suitably well in finding the level of volatility in the monthly series. Moreover, the P-GARCH(*1*, *1*) model was efficient for returns taken on the daily basis, whereas the GARCH(*1*, *1*) configuration was more accurate in making predictions on the weekly basis in the KSE 100 Index. Other researchers also found that good and bad news had a different impact on volatility (Javid & Mubarik, 2016). For KSE-100 Index all the asymmetric models were used but only EARCH model impacted leverage negatively. It established that good news increases volatility and bad news decreases volatility. Researchers concluded that volatility in Pakistani stock market index could be better modeled by asymmetric models.

Husain and Uppal (1999), while reviewing the variance of returns in stock markets in Pakistan, found that GARCH(*1*, *1*) was more appropriate in depicting the conditional variance, and also observed an evidence of perseverance in variance of KSE returns. Hameed et al (2006) also discovered that modeling of the conditional variance of stock returns of Pakistani Stock Index showed asymmetries and clustering. Mahmud and Mirza (2011) also used ARCH techniques in Karachi Stock Exchange and determined that the EGARCH(*1*, *1*) apprehended the asymmetric effect effectively during the financial crisis.

RESEARCH METHODOLOGY

The current study utilizes the time series data of the most cited stock index of Pakistan, i.e., the KSE 100 Index. For the purpose of analysis and in order to induce stationarity in the time series, returns were computed and used instead of the index points.

Since, as mentioned in the Introduction part of the paper, the primary objective was to check whether the future volatility in a given stock index can be forecasted by keeping in view its lagged variance, therefore, the ARCH-GARCH models were employed. As a first step, it was checked whether the time series under consideration was characterized by ARCH effects or not. After it was found that the series did involve periods of high and low volatility, it was subjected to ARCH tests in lower and higher orders. Following that, the GARCH test was also performed to make the model more parsimonious, yet more accurate. In addition, GARCH-M, TGARCH, and EGARCH were also estimated for the Index.

Daily figures of KSE 100 Index were taken and the data were obtained from ksestocks.com. Based on the availability of the data, the data for the said index was taken from Jan 01, 2010 until August 02, 2020 leading to 2660 observations.

ANALYSES AND FINDINGS

Like many time series variables, KSE 100 Index is also a non-stationary series and needs differencing in order to render it stationary. We, therefore, calculate its returns which automatically involves taking the first difference. After computing the returns, the next step is to check whether the series reflects any ARCH effects or not. To do this, a simple line graph is formed (see figure 1).

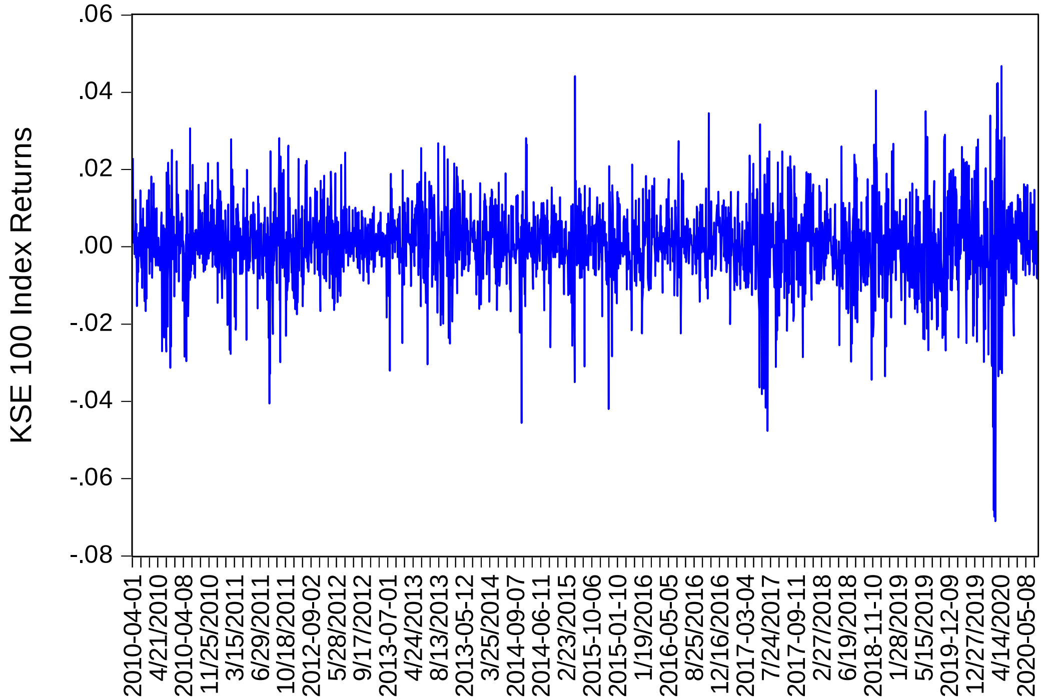

Figure 1: Plot of the Returns of KSE 100 Index

As can be seen, the graph clearly depicts evidence of ARCH effects in the time series under consideration. The series does not have a constant or equal variance over time. Therefore, ARCH models are safe and pertinent to be run.

Our analysis starts with estimation of an AR(*1*) model which is run through EViews using the ordinary least squares method:

Table 1: *An AR(1) Model for KSE 100 Index*

Dependent Variable: KSE Returns
Method: Least Squares
Sample (adjusted): 3 2661

Variable	Coefficient	Std. Error	t-Statistic	Prob.

C	.0005	.0001	2.384	.017
KSERETURNS(-1)	.143	.019	7.480	.000

R-squared	.021	Mean dependent var	.0005
Adjusted R-squared	.020	S.D. dependent var	.010
S.E. of regression	.010	Akaike info criterion	-6.339
Sum squared resid	.275	Schwarz criterion	-6.334
Log likelihood	8429.524	Hannan-Quinn criter.	-6.337
F-statistic	55.946	Durbin-Watson stat	2.000
Prob(F-statistic)	0.000		

The results of this regression are technically of no use to us. In fact, the residuals of this model are to be used to compute ARCH effects. As a starting point, we check for the effects of ARCH(*1*) presented in the table 2.

Table 2: *Testing for ARCH(1) Effects in the KSE 100 Index*

Heteroskedasticity Test: ARCH

F-statistic	60.513	Prob. F(1,2656)	.000
Obs*R-squared	59.209	Prob. Chi-Square(1)	.000

Dependent Variable: RESID^2
Method: Least Squares
Included observations: 2658 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	8.79E-05	5.40E-06	16.265	.000
RESID^2(-1)	.149	.019	7.779	.000

R-squared	.022	Mean dependent var	0.0001
Adjusted R-squared	.0219	S.D. dependent var	0.0003
S.E. of regression	.0002	Akaike info criterion	-13.678
Sum squared resid	.0001	Schwarz criterion	-13.673
Log likelihood	18179.70	Hannan-Quinn criter.	-13.676
F-statistic	60.513	Durbin-Watson stat	2.082
Prob(F-statistic)	.000		

The Obs*R-squared statistic, as can be seen in table 2, has a value of 59.209 with a high level of significance suggesting that the null hypothesis of no heteroskedasticity can be rejected, or that ARCH(1) effects are clearly there. But before we estimate the ARCH model, we will be testing for a higher order of ARCH effects using the OLS.

Table 3: *Testing for ARCH(4) Effects in the KSE 100 Index*

Heteroskedasticity Test: ARCH

F-statistic	98.859	Prob. F(4,2650)	.000
Obs*R-squared	344.740	Prob. Chi-Square(4)	.000

Dependent Variable: RESID^2
Method: Least Squares
Included observations: 2655 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4.79E-05	5.59E-06	8.569	.000
RESID^2(-1)	.046	.019	2.379	.017
RESID^2(-2)	.231	.019	12.093	.000
RESID^2(-3)	.159	.019	8.306	.000
RESID^2(-4)	.102	.019	5.259	.000

R-squared	.130	Mean dependent var	.0001
Adjusted R-squared	.129	S.D. dependent var	.0003
S.E. of regression	.0002	Akaike info criterion	-13.791
Sum squared resid	.0001	Schwarz criterion	-13.780
Log likelihood	18312.62	Hannan-Quinn criter.	-13.787
F-statistic	98.859	Durbin-Watson stat	2.042
Prob(F-statistic)	.000		

Table 3 presents the effects of ARCH(*4*). The Observed R-squared is now even higher (344.74, $p < 0.0001$) with all lags being highly significant. This obviously points out toward possible ARCH(*4*) effects in our variable of interest, i.e., the KSE 100 Index.

We will now be estimating an ARCH model to further confirm whether it will give better results or not. We start with ARCH(*1*) model.

Table 4: *An ARCH(1) Model for the KSE 100 Index*

Dependent Variable: KSE RETURNS
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Included observations: 2659 after adjustments
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = .7)
GARCH = C(3) + C(4)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	.0005	.0001	3.116	.002
KSERETURNS(-1)	.212	.012	17.322	.000
		Variance Equation		
C	7.62E-05	1.83E-06	41.707	.000
RESID(-1)^2	.297	.020	14.497	.000

R-squared	.016	Mean dependent var	0.000551
Adjusted R-squared	.0153	S.D. dependent var	0.010270
S.E. of regression	.0101	Akaike info criterion	-6.394906

Sum squared resid	.275956	Schwarz criterion	-6.386052
Log likelihood	8506.028	Hannan-Quinn criter.	-6.391702
Durbin-Watson stat	2.136651		

Table 4 shows that it took 11 iterations to reach convergence in model estimation. Note that the term "RESID(-1)^2" in the variance equation in the table represents ARCH(*1*). The coefficient of ARCH(*1*) is positive and highly significant (0.29, $p < 0.0001$) and so is consistent with our findings from the OLS method.

We will now be, of course, estimating a higher order ARCH configuration. Table 5 presents ARCH(*4*) results.

Table 5: *An ARCH(4) Model for the KSE 100 Index*

Dependent Variable: KSE RETURNS
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Included observations: 2659 after adjustments
Coefficient covariance computed using outer product of gradients
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	.001	.0001	5.725	.000
KSERETURNS(-1)	.188	.020	9.299	.000
		Variance Equation		
C	4.42E-05	1.99E-06	22.205	.000
RESID(-1)^2	.168	.021	7.802	.000
RESID(-2)^2	.179	.023	7.808	.000
RESID(-3)^2	.163	.021	7.860	.000
RESID(-4)^2	.083	.016	5.129	.000

R-squared	.016	Mean dependent var	.0005
Adjusted R-squared	.015	S.D. dependent var	.010
S.E. of regression	.010	Akaike info criterion	-6.502
Sum squared resid	.275	Schwarz criterion	-6.486
Log likelihood	8651.471	Hannan-Quinn criter.	-6.496
Durbin-Watson stat	2.084		

Again we have that all the ARCH coefficients are statistically significant and positive, a result consistent with our findings from the OLS regression. The conditional variance graph for the ARCH(4) model can be seen in figure 2.

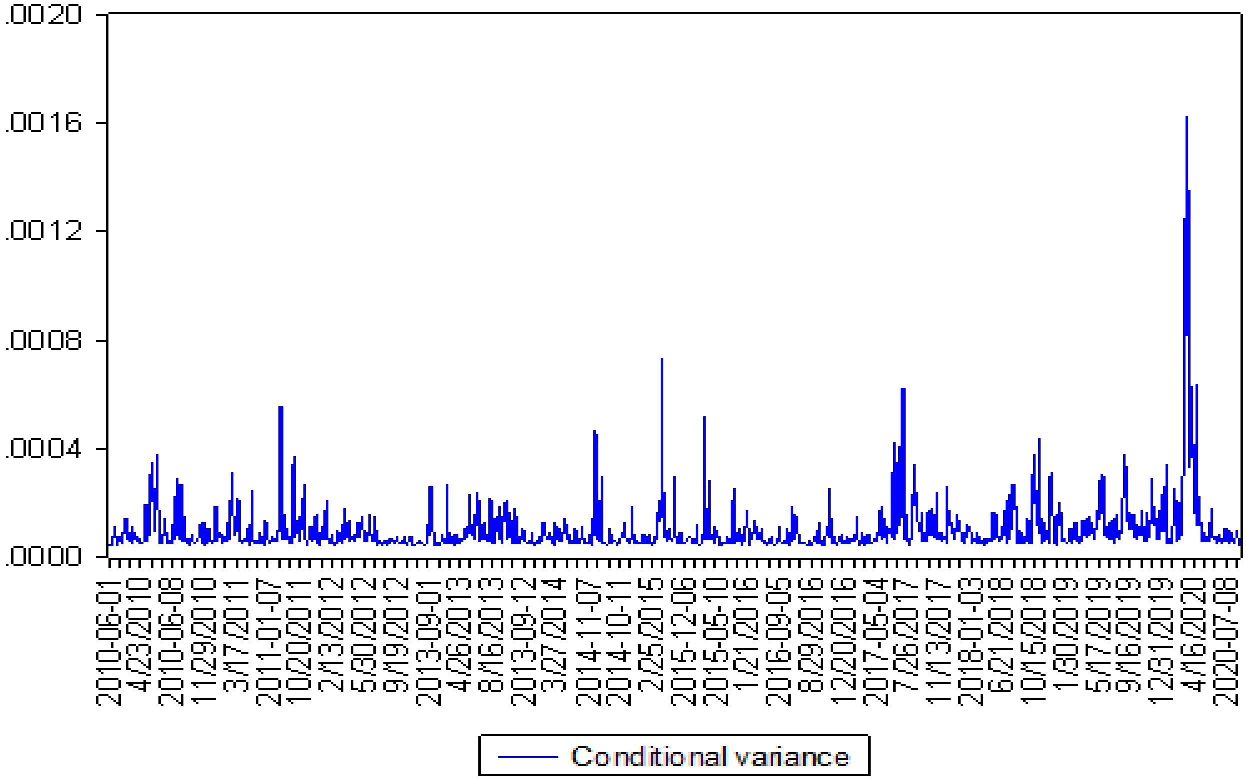

Figure 2: Conditional Variance Graph for an ARCH(4) model of the KSE 100 Index

ARCH(*q*) models often lack parsimony in that there are too many lags involved in them. Moreover, they look more like a moving average specification. We, therefore, now compute the GARCH(*p*, *q*) to introduce some simplicity in our model. In order to do that, we run the model again this time using the GARCH(*1*, *1*) specification to see whether the results get better or not.

Table 6: *A GARCH(1,1) Model for the KSE 100 Index*

Dependent Variable: KSE RETURNS
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Included observations: 2659 after adjustments
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = .7)
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	.001	.0001	5.803	.000
KSERETURNS(-1)	.181	.021	8.410	.000
		Variance Equation		
C	5.55E-06	8.16E-07	6.797	.000
RESID(-1)^2	.149	.014	10.907	.000

GARCH(-1)	.799	.017	46.817	.000
R-squared	.016	Mean dependent var		.0005
Adjusted R-squared	.016	S.D. dependent var		.010
S.E. of regression	.010	Akaike info criterion		-6.538
Sum squared resid	.276	Schwarz criterion		-6.527
Log likelihood	8697.069	Hannan-Quinn criter.		-6.534
Durbin-Watson stat	2.069			

As was noted earlier, the term “RESID(-1)^2” in table 6 represents the ARCH(*1*). It is obvious that the both the ARCH(*1*) and the GARCH(*1*) coefficients are positive and highly significant. The GARCH(*1*) has a very strong coefficient of almost 0.8 revealing that there are strong effects of the lagged conditional variance terms when taken as the autoregressive terms.

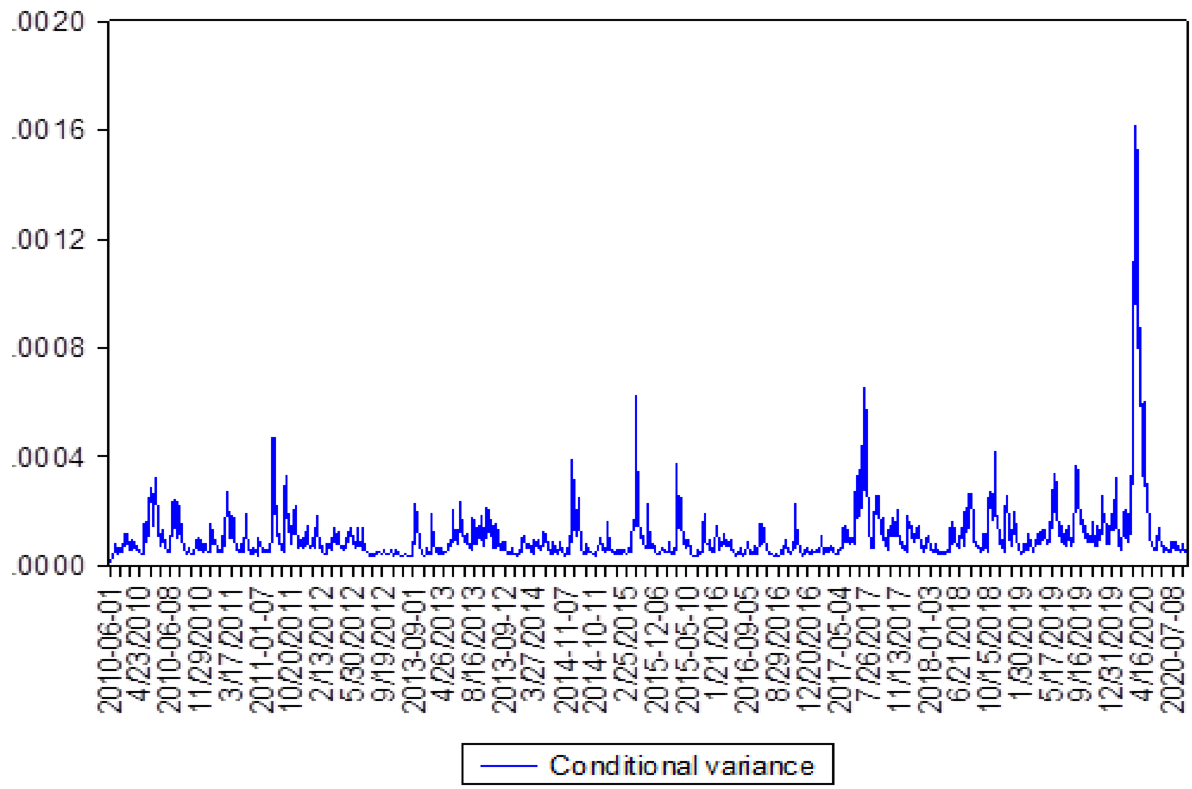

Figure 3: Conditional Variance Graph for a GARCH(1,1) model of the KSE 100 Index

Examining the graphs of ARCH(*4*) presented in figure 2 and that of GARCH(*1*, *1*) shown in figure 3, it can be easily inferred that the two patterns are very similar, if not perfectly identical, depicting that the GARCH is able to capture high orders of ARCH. Hence, estimating lower orders of GARCH than higher orders of ARCH is, of course, convenient, easy to interpret, as well as more accurate since it leads to the minimum loss of the degrees of freedom.

It is wise to check for higher orders of GARCH as well. We, therefore, try an over-parameterized GARCH(*4*, *4*) model.

Table 7: *A GARCH(4,4) Model for the KSE 100 Index*

Dependent Variable: KSE RETURNS
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Included observations: 2659 after adjustments
Coefficient covariance computed using outer product of gradients
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 + C(8)*GARCH(-1) +
C(9)*GARCH(-2) + C(10)*GARCH(-3) + C(11)*GARCH(-4)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	.001	.0001	5.837	.000
KSERETURNS(-1)	.184	.021	8.740	.000
		Variance Equation		
C	2.36E-05	3.86E-06	6.111	.000
RESID(-1)^2	.145	.016	9.139	.000
RESID(-2)^2	.181	.025	7.328	.000
RESID(-3)^2	.189	.020	9.459	.000
RESID(-4)^2	.091	.024	3.703	.000
GARCH(-1)	-.369	.081	-4.540	.000
GARCH(-2)	-.231	.048	-4.788	.000
GARCH(-3)	.108	.063	1.721	.085
GARCH(-4)	.665	.057	11.658	.000

R-squared	.016	Mean dependent var	.0005
Adjusted R-squared	.016	S.D. dependent var	.010
S.E. of regression	.010	Akaike info criterion	-6.540
Sum squared resid	.275	Schwarz criterion	-6.516
Log likelihood	8706.438	Hannan-Quinn criter.	-6.531
Durbin-Watson stat	2.076		

Table 7 presents the results of GARCH(*4*, *4*) model where now all the parameters are significant except for GARCH(*3*) which is slightly insignificant. There are, however, two negative GARCH terms in this model. Before we make a decision as to which model would be more suitable, let's try a GARCH(*1*, *4*) model as well.

Table 8: *A GARCH(1,4) Model for the KSE 100 Index*

Dependent Variable: KSE RETURNS
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Included observations: 2659 after adjustments
Coefficient covariance computed using outer product of gradients

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 + C(8)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	.001	.0001	5.742	.000
KSERETURNS(-1)	.180	.021	8.573	.000
		Variance Equation		
C	5.11E-06	9.98E-07	5.114	.000
RESID(-1)^2	.130	.021	6.260	.000
RESID(-2)^2	.025	.027	.907	.364
RESID(-3)^2	.016	.027	.605	.545
RESID(-4)^2	-.033	.023	-1.411	.158
GARCH(-1)	.814	.026	31.183	.000

R-squared	.016	Mean dependent var	.0005
Adjusted R-squared	.016	S.D. dependent var	.010
S.E. of regression	.010	Akaike info criterion	-6.536
Sum squared resid	.276	Schwarz criterion	-6.519
Log likelihood	8698.096	Hannan-Quinn criter.	-6.529
Durbin-Watson stat	2.068		

The GARCH(*1*, *4*) has three of its ARCH terms highly insignificant revealing again that the higher order ARCH terms are already captured by the GARCH(*1*, *1*) model. A comparison of the three models shows that ARCH(*1*, *1*) is slightly better than GARCH(*4*, *4*) and definitely better than GARCH(*1*, *4*) in that it has both (all) of its terms significant.

We now attempt to try a few other GARCH variants including the GARCH-M, the TGARCH, and the EGARCH models. We start with the GARCH-M, or the GARCH in Mean, model which allows the conditional mean to vary according to its very own conditional variance.

Table 9: *A GARCH-M(1,1) Model for the KSE 100 Index*

Dependent Variable: KSE RETURNS
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Included observations: 2659 after adjustments
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = .7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
GARCH	3.602	3.533	1.019	.308
C	.0007	.0003	2.279	.022
KSERETURNS(-1)	.180	.021	8.287	.000
		Variance Equation		
C	5.58E-06	8.16E-07	6.838	.000
RESID(-1)^2	.149	.014	10.889	.000
GARCH(-1)	.799	.017	46.842	.000

R-squared	.014	Mean dependent var	.0005
Adjusted R-squared	.013	S.D. dependent var	.010
S.E. of regression	.010	Akaike info criterion	-6.537
Sum squared resid	.276	Schwarz criterion	-6.524
Log likelihood	8697.636	Hannan-Quinn criter.	-6.533
Durbin-Watson stat	2.055		

The variance term (GARCH) in the mean equation in table 9 is insignificant. However, the inclusion of this term has increased the significance level of the GARCH term in the variance equation. We now see the results of the threshold GARCH (TGARCH) which adds a multiplicative dummy in the variance equation to check whether the difference between the positive and negative shocks is significant or not.

Table 10: *A TGARCH(1,1) Model for the KSE 100 Index*

Dependent Variable: KSE RETURNS
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Included observations: 2659 after adjustments
Coefficient covariance computed using outer product of gradients
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	.0005	.0001	3.402	.0007
KSERETURNS(-1)	.198	.019	10.036	.000
Variance Equation				
C	5.62E-06	6.89E-07	8.151	.000
RESID(-1)^2	.009	.010	.927	.353
RESID(-1)^2*(RESID(-1)<0)	.246	.023	10.454	.000
GARCH(-1)	.813	.016	51.607	.000

R-squared	.017	Mean dep. Var	.0005
Adjusted R-squared	.017	S.D. dependent var	.010
S.E. of regression	.010	Akaike info cri.	-6.585
Sum squared resid	.275	Schwarz criterion	-6.572
Log likelihood	8761.346	Hannan-Quinn cri.	-6.581
Durbin-Watson stat	2.108		

Since the coefficient of the "RESID(-1)^2*(RESID(-1)<0)" term in table 10 is positive and highly significant, it can be inferred that for KSE 100 Index there are asymmetries in positive and negative news. So bad news has a significantly larger impact on the volatility of stock index than good news.

Table 11: *An EGARCH(1,1) Model for the KSE 100 Index*

Dependent Variable: KSE RETURNS
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Included observations: 2659 after adjustments
Coefficient covariance computed using outer product of gradients

Presample variance: backcast (parameter = .7)
LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5)*RESID(-1)/@SQRT(GARCH(-1)) + C(6)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	.0005	.0001	3.319	.000
KSERETURNS(-1)	.194	.019	10.045	.000
		Variance Equation		
C(3)	-.783	.071	-10.955	.000
C(4)	.230	.021	11.057	.000
C(5)	-.162	.013	-12.820	.000
C(6)	.936	.007	136.029	.000

R-squared	.018	Mean dependent var	.0005
Adjusted R-squared	.018	S.D. dependent var	.010
S.E. of regression	.010	Akaike info criterion	-6.590
Sum squared resid	.275	Schwarz criterion	-6.577
Log likelihood	8767.477	Hannan-Quinn criter.	-6.585
Durbin-Watson stat	2.101		

We finally complete our analysis of the KSE 100 Index by computing EGARCH(*1*, *1*). Table 11 presents the results of the EGARCH model. All the C terms are highly significant indicating again that bad news at KSE 100 Index have deeper impacts on stock prices than good news.

CONCLUSION

The ARCH family of models were employed to model the variance of daily returns of KSE 100 Index. It was found that ARCH effects were present in the index and therefore techniques modeling the variance could present better results than those modeling the returns. Operationally, ARCH(*4*) model rendered better results than ARCH(*1*) or any other ARCH arrangement. As far as the GARCH modeling was concerned, the index was better off with the GARCH(*1*, *1*) configuration. Results of the GARCH-M model revealed that inclusion of the GARCH term in the mean equation had increased the significance level of the GARCH term in the variance equation for the index. Finally, the TGARCH and the EGARCH concluded that there were asymmetries in the positive and negative news for the KSE 100 Index. Hence, bad news was found to have a significantly larger impact on the volatility of the index under consideration than good news.

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