Kashmir Economic Review
Volume 25, No 1 -2016

Modeling Oil Price, Exchange Rate, and Interest Rate Volatility in Pakistan

Abdul Rashid[1] and Sidra Yaqub[2]

Abstract

The purpose of this study is to model and forecast volatility of Brent and West Texas Intermediate crude oil prices, nominal and real exchange rate, and money market rate and Treasury bill rate in the context of Pakistan. For this purpose, five linear and four non-linear models are used. The estimation period is January 1985 to December 2013. The in-sample estimation results show that the asymmetric GARCH family models well captured the volatility dynamics as compared to the symmetric GARCH models. We show that for NERR, RERR, MMR, and TBR linear models forecasted well as compared to the non-linear models. However, for both CBNR and WTIR, non-linear models forecasted well. Overall, this study concluded that linear models forecasted well as compared to the non-linear models on the basis of minimum value of RMSE. These findings are important for the policy makers, investors, and financial market participants for making appropriate policies, investment, and asset performance evaluation.

Keywords: Modeling volatility; Oil prices, Exchange rates, Interest rates, Linear versus non-linear models; in- and out-of-sample forecasts; RMSE; Pakistan
JEL Classification: Q02, Q40, Q41

1. Introduction

Understanding the volatile behavior of oil price, exchange rate, and interest rate has great importance in economics and finance. Specifically, knowledge of volatility helps in reducing risk because investors and traders can better manage their risk.[3] Further, the role of volatility in pricing their derivative securities cannot be ignored as one has to keep close eye on volatility of underlying asset from the date of buying until the expiry of the option (Poon and Granger, 2003; Chang, 2012; Wei et al., 2010; Kang et al., 2009).

Indeed, in recent decades, the emphasized on forecasting of volatility has considerably increased due to abrupt fluctuations in oil prices, exchange rate, and interest rate. Oil price, interest rate and exchange rate volatility are caused due to the crisis taking place over the time(Bruni (1983)). Modeling these unpredictable

[1] International Institute of Islamic Economics (IIIE), International Islamic University, Islamabad. Email: abdulrashid@iiu.edu.pk
[2] National University of Modern Languages, Islamabad. Email:sidra.baig17@yahoo.com
[3] For investors' point of view, high volatility means high risk, whereas, low volatility is considered as low risk. Thus, investors design their hedging strategies in alien with the extent of volatility.

economic and financial series is one of the main challenges for economists facing today. Shocks like world geopolitical tensions, stock market crash (1987), Gulf war (1990), Asian crisis (1997-1998), the September 11 attack (2001), worries over Iranian nuclear program, Iraq war in 2003, and the latest global financial crisis (2007-2009) affected significantly the mechanism of interest rate and exchange rate determination as well as oil pricing system.

Modeling and forecasting volatility of the oil price, the exchange rates, and the interest rates variables help policy makers for making policies in order to tackle the problems arising due to the volatile behavior of these variables (Musa et al. 2014). Uncertainties arising due to the oil price, exchange rates, and interest rates volatility affect not only individual investor's decision but also on all the institutions of the economy. Oil price, exchange rate, and interest rate fluctuations have several adverse impacts not only at the micro level but also at macro level. Volatility modeling and forecasting of these variables have important implications in resolving many issues. For example, trade imbalance, international capital budgeting problems, pricing derivatives, and balance of payment etc. The impact of natural calamity and financial or political crisis is far more as compared to the any good news. Through modeling and forecasting, we come to know what will be the future level of uncertainty. And thus, one can adopt precautionary measures according to the situation in order to, at least to some extent, reduce the upcoming risks.

The purpose of this study is to model and forecast the oil price, the exchange rate, and the interest rate volatility in Pakistan. Specifically, the study aims to examine the clustering, leverage effect, and persistence characteristics of these variables, five linear and four nonlinear models (GARCH family) are used in order to identify the model which effectively captures the volatility behavior of these variables.

2. Literature Review

A lot of studies have been done on modeling and forecasting oil price volatility by using GARCH family models. These studies covered a number of various issues by taking into account the important characteristics of oil markets in different respects (see Moshiri and Foroutan, 2006; Chang, 2012; Kang et al., 2009). In particular, Narayan and Narayan (2007) modeled the oil price volatility by using Exponential GARCH (EGARCH) model for capturing asymmetric behavior. They showed that there is inconsistency in capturing the asymmetric and persistent behavior of shocks across the various sub-samples and also across the full sample.

Cheong (2009) modeled and forecasted the volatility of Brent and WTI by using GARCH, APARCH, FIGARCH, and FIAPARCH models. They documented the evidence that there is existence of the persistence in both the WTI and Brent. However, they showed that the leverage effect is only present in the Brent crude oil market. Kang et al. (2009) forecasted the volatility of crude oil of Brent, WTI and Dubai by using daily data from 1992 to 2006. They used CGARCH, IGARCH, and FIGARCH models.[1]They also provided evidence of the existence of the volatility persistence in all the crude oil markets. Wei et al. (2010) extended the work of Kang at al. (2009) and applied nine linear and non-linear models for forecasting crude oil volatility of Brent and West Texas Intermediate. The in- and out-of-sample forecasting results showed that the nonlinear models perform well as compared to the linear class models.

Liu and Wan (2012) examined Shanghai fuel oil futures price volatility by using realized volatility and seminal GARCH class models. By using nonparametric method and high frequency data, this study found strong property of long range dependence. According to this study, EGARCH and GARCH (1, 1) models perform well in forecasting daily volatility among seminal GARCH class models. According to Mohammadi and Su (2010), the conditional standard deviation better captures the volatility as compared to the conditional variance by using GARCH, EGARCH, APARCH, and FIGARCH models.[2]They showed that EGARCH model ranked first in forecasting crude oil price volatility followed by APARCH model.

Hassan (2011) investigated the asymmetric behavior of crude oil by applying GARCH (1, 1), GARCH-M (1, 1), and EGARCH (1, 1) models. He concluded that shocks to crude oil prices are both asymmetric and persistent. Wang et al. (2011) studied the long memory property of the crude oil market of WTI by using different GARCH family models like GARCH (1, 1), GJR-GARCH, EGARCH, APARCH, and FIGARCH. They also used two non-parametric models, which are rescales rage analysis and detrended fluctuation analysis. They found that GARCH family models well captured the long memory property in WTI market for a long period of time. Yet, they showed that in case of short time period, the GARCH family models give misspecified results.

Salisu and Faasanya (2012) modeled the oil price volatility of WTI and Brent crude oil markets by taking into account the structural breaks. They used daily data from 2000 to 2012. They used GARCH (1, 1), GARCH-M (1, 1), TGARCH (1, 1), and EGARCH (1, 1) models. They successfully found two structural breaks of 1990 and 2008.[3] Their study also supported the evidence of the existence of the leverage and the persistence effects.

After the breakage of Bretton Wood system (1971) and the adoption of floating exchange rate system, there is a significant increase in the volatility of exchange rate. Alam (2012) forecasted the daily exchange rate volatility of BDT/USD and showed that the autoregressive model of order one performs

[1]Component GARCH model.
[2] APARCH stand for Asymmmetric Power ARCH model and FIGARCH stand for Fractionally Integrated GARCH model.
[3] Because of the Iraq and Kuwait conflict (1990) and global financial crisis (2008).

better in capturing the volatility in daily exchange rate. Akincilar *et al.,* (2011) investigated the forecasting ability of Turkey exchange rate and found that the best model for forecasting is Winter's method.

Hsieh (1989) found that EGARCH model perform well as compared to the other GARCH class models in removing conditional heteroscedasticity. Balaban (2004) forecasted the daily exchange rate volatility by using different symmetric and asymmetric models. Their results revealed that EGARCH model outperforms in capturing and forecasting volatility.

Abdalla (2012) modeled dynamics of daily exchange rate of the nineteen Arab countries by using GARCH (1, 1) and EGARCH (1, 1). The results of EGARCH model show that there is existence of leverage effect in all the countries. Olowe and Ayodeji (2009) investigated the properties of persistence and asymmetry of Naira/Dollar exchange rates by using GARCH family models. They found that there is volatility persistence and among the GARCH family models, APARCH (1, 1) performs better in capturing the asymmetric behavior in manages float regime. Bala and Asemota (2013) examining the volatility of monthly exchange rate concluded that those GARCH models that incorporate volatility breaks perform better as compared to models that do not take into account volatility breaks.

Mckenzie (1997) analyzed the dynamics of daily exchange rate by APARCH model. They found that the in case of symmetric data, the standard GARCH (1, 1) model performs better, whereas, in case of asymmetric data, APARCH model outperforms. Brooks and Burke (1998) estimated the forecasting ability of US dollar exchange rate by using GARCH (1, 1) and modified information criterion (MIC). The results obtained by using MIC reveal that the GARCH (1, 1) model outperforms in out-of-sample forecasting. Musa et al. (2014) modeled and forecasted the daily exchange rate of Nigeria/USD from period 1991 to 2013 by using different GARCH family models and forecasting criteria. On the basis of maximum log likelihood value, minimum AIC, and forecasting criteria, they concluded that the TS-GARCH model best captured all the stylized features of Nigeria/Dollar exchange rate and recommended that the GARCH family model performs well in forecasting and capturing the dynamics qualities of exchange rate.[1]

Relatively a few studies have been done on capturing the volatile behavior of the exchange rate in Pakistan. For example, Kamal et al. (2012) examined the volatility of daily and monthly Pak exchange rate by using GARCH family models for the period of 2001 to 2009. According to their results based on GARCH-in-mean model, there is no trade-off between risk and return in both daily and monthly exchange rate. Their EGARCH model results provide evidence of asymmetric behavior of exchange rate. Malik (2011) forecasted the

[1] TS-GARCH stands for Time Switching GARCH model.

exchange rate volatility of Pakistan by using different univariate and multivariate models by using monthly data from 2000 to 2010. He found that the ARCH model ranked first in forecasting the exchange rate volatility. Ramzan *et al.,* (2012) modeled and forecasted the exchange rate behavior of Pakistan by using monthly data spanning 1981-2010. Their results unveiled that among the ARCH family models, GARCH (1, 2) best captured the persistence effect, while leverage effect was more accurately explained by the EGARCH (1, 2)

Several prior studies have examined the volatility behavior of interest rate by using different models. For example, Edward and Susmel (2003) used SWARCH model, whereas,Koutmos (2012) used the extended EGARCH model. Both of these studiesfound that the innovations play more important role in interest rate volatility as compared to the level of interest rate. They further concluded that there was high persistence in the Treasury bill rates of US. Covarriubias *et al.,* (2006) modeled and forecasted the volatility in yield of 10 years US Treasury note. They found that by incorporating regime shifts in the GARCH (1, 1) model reduces the volatility persistence and this model outperform in case of under predictions during out-of-sample forecasting. Hegerty (2014) examined the monthly nominal interest rate volatility and spillover effects for Latin American countries. The results showed that the GARCH (1, 1) and EGARCH (1, 1) models are best in capturing the volatile behavior of nominal money market rate.

Irfan *et al.,* (2010) examined the volatility pattern of Karachi interbank offering rate and Mumbai interbank offering rate. The used GARCH, EGARCH, PARCH, and TGARCH models. The in-sample estimation results show that the EGARCH and PARCH models are best for capturing the asymmetric behavior of volatility and KIBOR is more volatile as compared to the MIBOR. The RMSE and MAE showed that the MIBOR's forecast is better as compared to the KIBOR

In sum, there are a lot of studies on modeling and forecasting volatility behavior of these variables by using linear and non-linear models in developed and emerging economies (as mention in the literature above). However, only a few studies have been done on Pakistan (Irfan et al., 2010; Mudakkar *et al.,* 2013; Kamal *et al.,* 2012). Most of the studies of Pakistan have used different econometrics techniques, and frequency of data for modeling and forecasting volatility of financial series (Shah *et al.,* 2009; Pasha *et al.,* 2007; and Hassan, 2013).

This study uses both linear and non-linear models. There is none of the study on Pakistan which model and forecasted all these highly volatile variables from three different markets; commodity market, forex market, and credit market by using both linear and non-linear models on a single platform. So, this study fulfill this gap by using linear and nonlinear models for modeling and forecasting volatile behavior of oil price, exchange rate, and interest rate.

3. Model Specification and Methodology

In this study, five linear models are used for estimation in order to know that which model is best for modeling and forecasting oil price, exchange rate, and interest rate volatility. These models are following.

Random Walk

Random walk model is a non-stationary process.[1] According to this model, yesterday's observed volatility gives the best forecast of today's volatility. This process can be represented as:

$$X_t = X_{t-1} + \varepsilon_t \quad (1)$$

where X_t is the value of the series at time t and ε_t is the error term.

Autoregressive (AR) Model

Autoregressive model of first order AR (1) is the simplest and most frequently used model. It represents a type of random process in which the future observations rely on the recent past. The AR (1) process is given as:

$$X_t = \mu + \alpha X_{t-1} + \varepsilon_t \quad (2)$$

where X_t represents the actual rate of return at period t. ε_t are called the error terms or innovations, μ is constant. α represents the parameters of the model with values ranges from -1 to 1

Moving Average (MA) Model

In moving average forecasting model, current forecast depends on the lagged values of the forecast error. It is expressed as follows.

$$X_t = \mu + \alpha_1 \varepsilon_{t-1} + \varepsilon_t \quad (3)$$

whereα_1 is moving average parameter and its absolute value must be less than one and μ is constant term. $\varepsilon_t$andε_{t-1} are the residuals at time t and $t-1$.

Simple Exponential Smoothing Model

Exponential smoothing technique was introduced by Brown (1956). Exponential smoothing technique depends only on the current and past values of the series and may be used to forecast the future value. Simple exponential smoothing equation is given by:

$$S_t = \alpha Y_t + (1-\alpha)S_{t-1} \quad (4)$$

where S_t is the smoothed series andα is a smoothing factor. $0 < \alpha < 1$ andY_t is a sequence of raw data observations at time t. If the value of α is small then it gives more smoothing and if the value of α is larger then it gives less smoothing. If the value of α is closer to 1 then S_t is closer to Y_t and if the value of α is closer to zero then the S_t is closer to S_{t-1}.

Double (Holt) Exponential Smoothing Model

Double exponential smoothing model is used to smooth an already smoothed time series. When there is trend in the data then simple exponential smoothing technique does not work well. So, double exponential smoothing technique is used.

[1]Because mean is constant but variance changes with the passage of time.

$$S_t = \alpha Y_t + (1-\alpha)(S_{t-1} + b_{t-1}) \tag{5}$$
$$b_t = \beta(S_t - S_{t-1}) + (1-\beta)b_{t-1} \tag{6}$$

where β and α are the forecasting parameters. $\beta$is the trend smoothing factor and α is for the constant term. Value of these forecasting parameters lies between 0 and 1.$Y_t$represents the raw data sequence.

Specification of Non Linear Model: The GARCH Model

According to this model, conditional variance depends on not only on the lagged squared error terms but also on its own lagged conditional variance. The equation for GARCH (1, 1) model is as follows:

Mean equation:

$$r_t = \mu_t + \varepsilon_t \tag{7}$$

Variance equation:

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{8}$$

In order to ensure that that the conditional variance is positive, certain restrictions are imposed on the parameters which are $\omega > 0, 0 < \alpha_1 < 1$, and $0 < \beta_1 < 1$. And $\alpha_1 + \beta_1 < 1$ then it means that the volatility will die out over time and if $\alpha_1 + \beta_1 = 1$ then it means that the volatility will persist forever.

The GARCH-M Model

The added advantage of the GARCH–M model which was purposed by Engle et al. (1987) is to test whether variance can impact mean of future returns. The obvious difference between the GARCH-M and GARCH (1, 1) is that the variance appears in the mean equation. So in this study, GARCH-M model is used.

Mean equation:

$$r_t = \mu_t + \delta\sigma_t^2 + \varepsilon_t \tag{9}$$

Variance equation:

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{10}$$

whereσ_t^2 is conditional variance with parametric restrictions $\omega > 0$, $0 < \alpha_1 < 1$, and $0 < \beta_1 < 1$.$\alpha_1 + \beta_1 < 1$ and is used to capture the volatility persistence. $\mu$is the conditional mean.δrepresents the risk premium which is an indication of the nature of relationship between risk and return.

The EGARCH Model

Exponential GRACH model by Nelson (1991) has certain advantages over the GARCH model. First, it does not impose restrictions on ω ,γ_1, and β_1 like the GRACH model. Second, it captures the asymmetric behavior of volatility. It means that positive shocks results in higher volatility than negative shocks, and vice versa.

Mean equation:

$$r_t = \mu_t + \varepsilon_t \tag{11}$$

Variance equation:

$$\ln(\sigma_t^2) = \omega + \alpha_1(|\varepsilon_{t-1}| + \gamma_1 \varepsilon_{t-1}) + \beta_1 \ln(\sigma_{t-1}^2) \quad (12)$$

whereγ_1 is used to captures the asymmetric leverage effect. If the value of γ_1 is negative then it means that negative shocks reduces volatility more than the positive shocks and if $\gamma_1 = 0$ then there is symmetric effect and there will be no asymmetric effect. $\beta_1$estimates the persistence of shocks.

The PARCH Model

The PARCH model used in this study is asymmetric power ARCH (PARCH) model purposed by Ding et al. (1993). This model directly parameterizes the non-linearity in the conditional variance (using θ). The PARCH (p, q) model is defined as:

Mean equation

$$r_t = \mu_t + \varepsilon_t \quad (13)$$

Variance equation:

$$\sigma_t^\theta = \omega + \alpha_1 (|\varepsilon_{t-1}| - \gamma_1\varepsilon_{t-1})^\theta + \beta_1(\sigma_{t-1})^\theta \quad (14)$$

where parametric restrictions is $\omega > 0$, $\beta \geq 0$, and $\theta \geq 0$ andθ represents the power. $\gamma_1$reflects the leverage effect and it should be greater than -1 but less than 1. $\varepsilon_{t-1}$is the shock term of previous period.

Data Description and Sources

The proxy used for exchange rate is real exchange rate (RERR) and nominal exchange rate (NERR) of Pakistan. Money market rate (MMR) and Treasury bill rate (TBR) are used as a proxy for the interest rate of Pakistan. Brent (CBNR) and West Texas (WTIR) oil prices are used as a proxy for oil prices. The study covers the period from January 1985 to December 2013, consisting of total 348 observations for all variables except the TBR. Since Treasury bill rate first time auctioned in March 1991, so, the data on Treasury bill rate is from 3rd March 1991 to December 2013 consisting of total 274 observations. The data are divided into in-sample estimation consisting of 324 observations and out-of-sample forecasting by using last 24 observations for all variables except the TBR. The numbers of observations used for in- and out-of-sample forecasting in case of TBR are 250 and 24, respectively. All the data are obtained from International Financial Statistics (IFS).

All the underlying variables are converted into returns series on continuous compounding. Specifically, the returns are defined as follows:

$$Y_{it} = \ln\left({}^{X_{it}}/_{X_{it-1}}\right) \times 100$$

whereY_{it} represents the return at time t. X_{it} denotes the price of underlying series (i.e., oil prices and the exchange rate) at time t. X_{it-1} denotes the price of underlying series at time $t-1$.

4. Estimation Results:

The descriptive statistics suggest that NERR, RERR, and MMR are positively skewed, meaning having fatter right tails. However, TBR, CBNR, and WTIR are negatively skewed. Since the value of skewness is close to zero for only MMR, so, the distribution of MMR is normal. NERR, RERR, TBR, CBNR and WTIR exhibit high kurtosis except the MMR. The null hypothesis of Jarque-Bera (JB) test statistics is that the given series is normally distributed. As one can see from the table, the null hypothesis is rejected for all the series except the MMR, which is an evidence of non-normal distribution.

Table 1. Descriptive Statistics of the Return Series

Variables	Statistics							
	Mean	Max	Min	Std.dev	skewness	Kurtosis	Jarqe-Bera	Prob.
NERR	0.005	0.121	-0.035	0.017	3.577	21.318	5591.100	0.000
RERR	0.010	0.120	-0.041	0.019	2.530	12.997	1815.252	0.000
MMR	0.086	0.200	0.007	0.034	0.110	3.063	0.758	0.685
TBR	10.320	17.420	1.210	3.558	-0.794	3.423	30.847	0.000
CBNR	0.004	0.433	-0.383	0.092	-0.240	5.937	128.069	0.000
WTIR	0.004	0.376	-0.397	0.085	-0.431	6.090	148.814	0.000

The results of the ADF-GLS tests are reported in Table 2. The unit root tests support the evidence of stationarity of NERR, RERR, CBNR, and WTIR at levels and only TBR and MMR become stationary by taking first difference. Figures 1 to 6 provide evidence that all the series possesses volatility and volatility clustering behavior.

Table2: Results of the Augmented Dickey-Fuller GLS Test

Variables	Level		Difference	
	Intercept	Intercept and Trend	Intercept	Intercept and Trend
NERR	-3.496***	-3.571***		
RERR	-2.334**	-2.933**		
MMR			-2.747***	-5.400***
TBR			-2.051**	-2.911**
CBNR	-8.944***	-9.544***		
WTIR	-11.225***	-13.169***		

Note: ***denotes the significance at the 1% level, **denotes the significance at the 5% level, and*denotes the significance at the 10% level. The results of MMR are significant by taking lag length of 4. TBR become significant at 5% level on intercept by taking lag length 2 while in case of trend and intercept it is significant at the 5% level by taking lag length 4.

Fig. 1. Monthly Returns of the CBNR

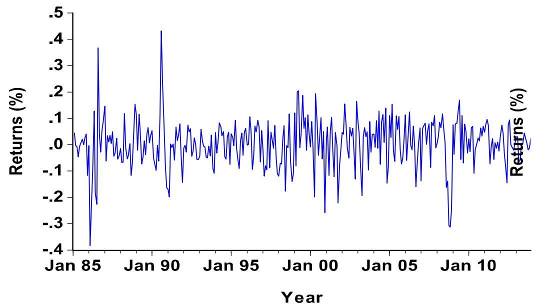


Fig. 2. Monthly Returns of the WTIR

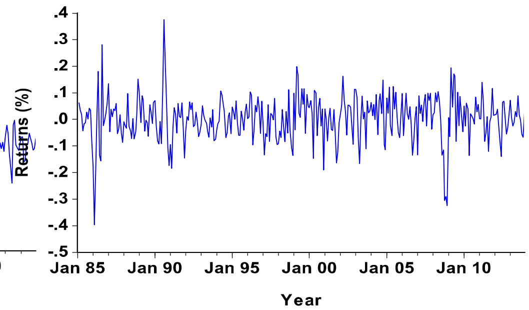


Fig. 3. Monthly Returns of the NERR

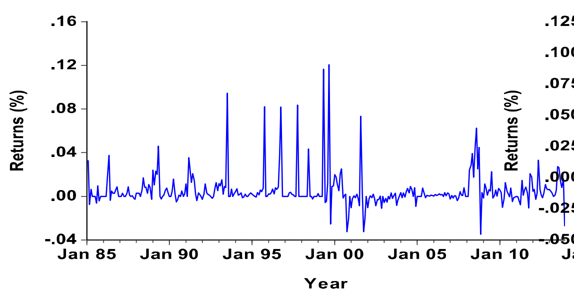


Fig. 4. Monthly Returns of the RERR

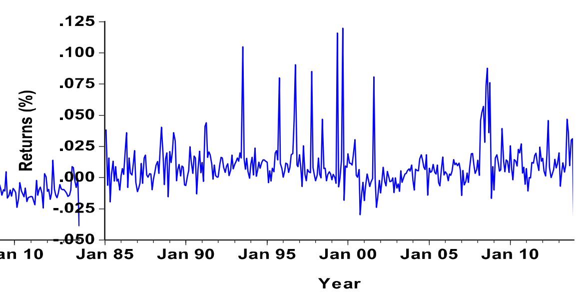


Fig. 5. TBR at First Difference

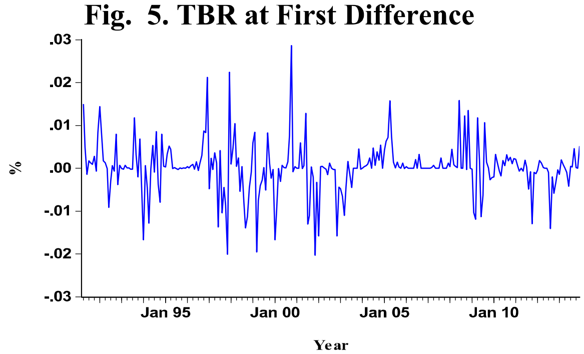
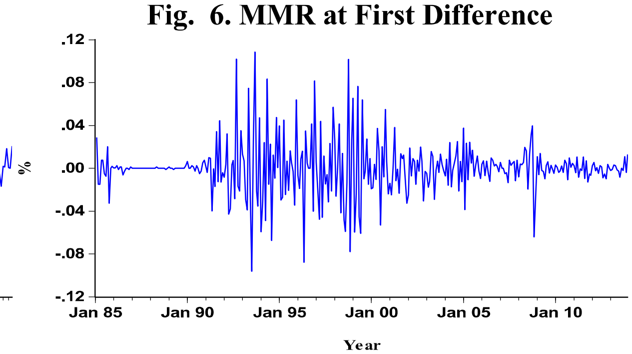


Fig. 6. MMR at First Difference



Results of Linear Models

The results of the RW model are given in Table 3. Consistent with Geman (2007), we found that none of the underlying series follows random walk process. The results of the AR model are shown in Table 4. The order of autoregressive model for all the variables is one except the NERR. However, in case of NERR, four lagged values are included in the specification. All the underlying series are stationary as the value of their coefficients is less than one.

The results of the MA model are shown in Table 5. The value of coefficients of MA for NERR, RERR, MMR, TBR, CBNR, and WTIR are all positive and significant at the 1% level l. These findings are consistent with the findings of Akincilar et al. (2011). The value of the coefficients of all underlying series, which is less than one, suggest that socks have temporary effects on the volatility and die out with the passage of time.

Table 3: Results of the RW Model

Variables	Coefficients	Std. error	Log Likelihood	AIC
NERR	0.1726***	0.0547	847.7693	-5.2594
RERR	0.3590***	0.0518	802.4522	-4.9779
MMR	-0.3184***	0.0532	736.7012	-4.5695
TBR	0.1815***	0.0618	910.1066	-7.3315
CBNR	0.2225***	0.0544	312.3363	-1.9337
WTIR	0.2955***	0.0532	344.6551	-2.1345

Note: *** denotes the significance at the 1% level.

Table 4: Results of the AR (1) Model

Variables	M	Coefficient of AR	Std. error	Log likelihood	AIC
NERR	0.0054	0.1982***	0.0549	855.6801	-5.3522
RERR	0.0099	0.1863***	0.0547	824.2775	-5.1071
MMR	-0.0076	-0.3184***	0.0528	736.7013	-4.5633
TBR	009.81	0.1811***	0.0619	910.1276	-7.3236
CBNR	0.0041	0.2209***	0.0545	312.5318	-1.9287
WTIR	0.0039	0.2940***	0.0533	344.8337	-2.1294

Table 5: Results of the MA (1) Model

Variables	M	Coefficient of AR	Std. error	Log likelihood	AIC
NERR	0.0054	0.2271***	0.0544	867.2843	-5.3577
RERR	0.0100	0.1557***	0.0551	825.1593	-5.0969
MMR	0.0009	0.6444***	0.0427	757.7449	-4.6795
TBR	0.0002	0.1703***	0.0626	911.0654	-7.3017
CBNR	0.0043	0.2295***	0.0543	314.0785	-1.9323
WTIR	0.0042	0.2808***	0.0535	345.3665	-2.1261

Note: *** means significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level. In case of RERR, MA (4) is used because results are significant at MA (1).

The out-of-sample forecasting results of the SES model are given in Table 6. The results showed that the values of alpha for NERR, RERR, MMR, TBR, CBNR, and WTIR are closer to the zero. This is an indication that the future observations for all the variables are closer to the forecasted value of the last observation. The out-of-sample forecasting shows that the value of RMSE is minimum for the CBNR. The out-of-sample forecasting results of the DES model are reported in Table 7. The out-of-sample forecasting shows that the value of RMSE is lowest for WTIR.

Table 6: Out-of-Sample Forecasting Results of the SES Model

Variables	Alpha	RMSE
NERR	0.001	0.0114
RERR	0.010	0.0177
MMR	0.100	0.0055
TBR	0.30	0.0037
CBNR	0.001	0.0622
WTIR	0.10	0.0554

Note: RMSE is the root mean error square. The value of alpha should be greater than zero but less than one.

Table 7: Out-of-Sample Forecasting Results of the DES Model

Variables	Alpha	Beta	RMSE
NERR	0.1	0.1	0.0177
RERR	0.1	0.2	0.0187
MMR	0.01	0.59	0.0057
TBR	0.2	0.1	0.0038
CBNR	0.1	0.1	0.0572
WTIR	0.1	0.17	0.0589

Note: Beta measures the trend in the data. The value of beta and alpha greater than zero but should be less than one. RMSE is the root mean error square.

Empirical Results for the GARCH Family Models: Testing for ARCH Effects Detection of ARCH effect and serial correlation is most important before applying the GARCH family models. Table A1 given in the appendix shows the test statistics for testing the existence of the ARCH effect and serial correlation. The Ljung-Box Q-statistics purposed by the Ljung and Box (1978) is used to check the serial correlation in the return series. The null hypothesis of no serial correlation is rejected for all the series. This provides the evidence of the existence of serial correlation in the residuals for all the underlying variables up to lags 5, 10, 20, and 50. This finding suggests the use of ARMA process in the mean equation while estimating GARCH family models.

The estimated values of Ljung Box Q-squared statistics suggest that the null hypothesis of no serial correlation is rejected for all underlying series in case of Q-squared statistics up to 50 lags. The results of LM-ARCH test show that the null hypothesis of no ARCH effect is rejected for all underlying series. Thus, there is strong evidence of the presence of ARCH effect in all the said series.

In-Sample Estimation Results of the GARCH (1, 1) Model

The in-sample estimation results of GARCH (1, 1) model are given in Table 8. The results show that all the mean and variance equations parameters are statistically significant. The value of $\alpha_1 + \beta_1$ measuring the persistence effect is greater than zero but less than one for both the CBNR and WTIR, which is in line with the previous literature (Kang *et al.,* 2009; Hassan, 2011; Salisu and Fasanya 2012; Mohammadi and Su, 2010). It also means that the shocks to the conditional variance do not have permanent effect on the volatility and die out with the passage of time which is consistent with the findings of Wei *et al.,* (2010). The response of CBNR and WTIR volatility is symmetric to past shocks.

The in-sample estimation results of GARCH (1, 1) model for NERR and RERR show that the values of α_1 and β_1 measuring the ARCH and GARCH effects are statistically significant. The value of $\alpha_1 + \beta_1$ is close to one for NERR, which means that shocks to the volatility of NERR are highly persistent and it is in line with the previous literature (Abdalla, 2012; Hseih, 1989). However, for RERR, the shocks die out with the passage of time as the value of $\alpha_1 + \beta_1$ is 0.6632. The in-sample estimation results of the GRACH (1, 1) model for the MMR and TBR show that the value of $\alpha_1 + \beta_1$ is greater than zero. It means that shocks have permanent effect on the volatility of both MMR and TBR for all future time periods. As the process of conditional variance is explosive, we do not do any further analysis for these two series. Diagnostic test results are given in Table A2 in the appendix provide evidence of no serial correlation and volatility clustering up to 50 lags. The value of ARCH-LM test shows that there is no ARCH effect remaining in the series.

Table 8: Results for the GARCH (1, 1) Model

Variables	CBNR	WTIR	NERR	RERR	MMR	TBR
Model	GARCH (1,1)	GARCH (1,1)	GARCH (1,1)	GARCH (1,1)	GARCH (1,1)	GARCH (1,1)
Mean Equation						
Constant	0.0042 (0.3645)	0.0058 (0.1694)	0.0048*** (0.001)	0.0097*** (0.000)	0.0084 (0.906)	0.0007 (0.254)
AR	0.1734*** (0.008)	0.2064*** (0.002)	0.1884*** (0.000)	0.2385*** (0.001)	0.2934** (0.024)	0.2378*** (0.001)
MA	-0.1771*** (0.001)	- 0.1536*** (0.004)			-0.6400*** (0.000)	0.2096*** (0.026)
Variance equation						
ω	0.0015*** (0.013)	0.001434** (0.047)	0.0830*** (0.000)	0.0021*** (0.000)	0.0002*** (0.000)	0.0024*** (0.000)
α_1	0.2786*** (0.000)	0.2631*** (0.000)	0.0309*** (0.000)	0.1481*** (0.004)	0.6622*** (0.000)	0.2826*** (0.000)
β_1	0.5525*** (0.000)	0.5302*** (0.000)	0.9416*** (0.000)	0.5151*** (0.000)	0.5696*** (0.000)	0.7280*** (0.000)
$\alpha_1 + \beta_1$	0.8312	0.7933	0.9725	0.6632	1.2319	1.0106
Log Likelihood	334.7394	368.7335	870.8444	837.3528	948.0065	935.2858
Akaike Criteria	-2.0418	-2.2530	-5.4284	-5.1698	-5.8509	-7.4942

Note: *** denotes the significance at the 1% level, ** denotes the significance at the 5% level, and * denotes the significance at the 10% level. The numbers in the brackets are p-values.

In-Sample Estimation Results of the GARCH-M (1, 1) Model

The results of the in-sample estimation of the GARCH-M (1, 1) model for are given in Table 9. All the variance equations parameters are significant. However, in the mean equation, the value of δ measuring the risk premium is not significant for both the CBNR and WTIR. This means that there is no trade off between risk and return. This finding is in line with the findings of Hassan (2011). The sum of $\alpha_1 + \beta_1$ for both the CBNR and WTIR is significant and less than zero. This implies that the persistence effect is not permanent and volatility although takes a long time but does return to its mean in case of both CBNR and WTIR.

The table shows that the aggregate of$\alpha_1 + \beta_1$is less than one for both the NERR and RERR ensuring the stationarity of the data. The value of δ measuring the risk premium in case of GARCH-M (1, 1) model is insignificant for both the NERR and RERR. The value of $\alpha_1 + \beta_1$ is greater than zero for both MMR and TBR, which is an indication that the conditional variance is an explosive process.

The results of diagnostic tests given in Table A3 in the appendix do not provide any significant evidence of the presence of serial correlation in the residuals. The ARCH-LM test results also indicate that there are no remaining ARCH effects.

Table 9: Results for the GARCH-M (1, 1) Model

Variables	CBNR	WTIR	NERR	RERR	MMR	TBR
Model	GARCH-M(1,1)	GARCH-M(1,1)	GARCH-M(1,1)	GARCH-M(1,1)	GARCHM(1,1)	GARCH-M(1,1)
Mean Equation						
δ	0.1737 (0.537)	0.1417 (0.646)	0.0312 (0.932)	-0.4224 (0.548)	-0.0278 (0.433)	-0.3321 (0.723)
Constant	-0.0097 (0.670)	-0.0043 (0.8445)	0.0044 (0.393)	0.0170 (0.157)	0.0003 (0.428)	0.0019*** (0.039)
AR	0.1811*** (0.007)	0.2139*** (0.001)	0.2061* (0.070)	0.2802*** (0.003)	0.2923** (0.024)	0.2326*** (0.001)
MA	-0.1726*** (0.001)	-0.1494*** (0.007)			-0.6433*** (0.000)	0.2142*** (0.020)
Variance equation						
ω	0.0015*** (0.012)	0.0013** (0.055)	0.0116*** (0.000)	0.0001*** (0.000)	0.0172*** (0.000)	0.0024*** (0.002)
α_1	0.2730*** (0.000)	0.2571*** (0.000)	0.0632*** (0.000)	0.1406*** (0.010)	0.6616*** (0.000)	0.2712*** (0.000)
β_1	0.5585*** (0.000)	0.5404*** (0.000)	0.9038*** (0.000)	0.5170*** (0.000)	0.5702*** (0.000)	0.7425*** (0.000)
$\alpha_1 + \beta_1$	0.8316	0.7976	0.9610	0.6777	1.2321	1.0138
Log Likelihood	334.9699	368.8530	860.1265	837.7442	948.2137	937.1648
Akaike Criteria	-2.0730	-2.2475	-5.3550	-5.1661	-5.8460	-7.5013

Note: *** denotes the significance at the 1% level, ** denotes the significance at the 5% level, and * denotes the significance at the 10% level.

In-Sample Estimation Results of the EGARCH (1, 1) Model

Table 10 presents the results of EGARCH (1, 1) model. The estimates provide evidence of the presence of the leverage effects in both the CBNR and WTIR. The value of γ measuring the leverage effect is negative and statistically significant for both the CBNR and WTIR at 5% and 10% significant level. It means that the positive and negative news do not have same effect on volatility. Volatility increases more by bad news as compared to the good news in crude oil markets and are in line with the literature (Hassan, 2011 Narayan and Narayan, 2007; Mohammadi and Su, 2010; Khan and Asghar, 2010). The diagnostic tests show that there is no ARCH effect and so serial correlation as indicated by the ARCH-LM and Q-statistics on standardized and squared standardized residuals.

One can see from the table that all the mean as well as variance equations parameters of EGARCH (1, 1) model are statistically significant for both the NERR and RERR. The value of leverage parameter γ is significant but positive for both the NERR and RERR. It means that there is existence of leverage effect and shocks have asymmetric effects on the volatility of NERR and RERR.

The value of γ measuring the leverage effect is insignificant for both MMR and TBR, which implies that shocks have symmetric effect on the volatility of MMR and TBR. The value of β_1 is very close to one for both the MMR and TBR indicating that the shocks to the volatility are quite high and last far into the future for a long period of time. All the estimated models pass the diagnostic tests.

Table 10: Results for the EGARCH (1, 1) Model

Variables	CBNR	WTIR	NERR	REER	MMR	TBR
Model	EGARCH (1,1)	EGARCH (1,1)	EGARCH (1,1)	EGARCH (1,1)	EGARCH (1,1)	EGARCH (1,1)
Mean Equation						
C	0.0019 (0.704)	0.0033 (0.452)	0.0045*** (0.008)	0.0100*** (0.000)	-0.0001* (0.074)	0.0010** (0.0371)
AR	0.2085*** (0.002)	0.2276*** (0.001)	0.1840*** (0.000)	0.2244** (0.022)	-0.3426*** (0.000)	0.2717*** (0.000)
MA	-0.1514*** (0.005)	-0.1330*** (0.019)	0.2296*** (0.001)		-0.2712*** (0.000)	0.1261*** (0.000)
Variance equation						
Ω	-1.5184*** (0.001)	-1.3615*** (0.011)	-2.7373*** (0.000)	-2.6516*** (0.000)	-0.9467*** (0.000)	-2.0828*** (0.000)
α_1	0.4778*** (0.000)	0.3842*** (0.000)	-0.1463*** (0.003)	0.1679*** (0.017)	0.8368*** (0.000)	0.4937*** (0.000)
β_1	0.7662*** (0.000)	0.7933*** (0.000)	0.6634*** (0.000)	0.6833*** (0.000)	0.9626*** (0.000)	0.8290*** (0.000)
Γ	-0.0919** (0.057)	-0.1090* (0.082)	0.3776*** (0.000)	0.1593*** (0.001)	0.0553 (0.231)	0.0842 (0.108)
Log Likelihood	335.8083	369.7199	875.5417	839.8575	942.8783	938.9607
Akaike Criteria	-2.0422	-2.2529	-5.4454	-5.1792	-5.8129	-7.5158

Note: *** denotes the significance at the 1% level, ** denotes the significance at the 5% level, and * denotes the significance at the 10% level.

In-Sample Estimation Results of the APARCH (1, 1) Model

The in-sample estimation results of the APARCH (1, 1) model are reported in Table 11. The values of α_1 , β_1 and $\alpha_1 + \beta_1$ are statistifically significant for both the CBNR and WTIR. The value of γ measuring the leverage effect is not statistically significant for both the CBNR and WTIR. It means that there is no leverage effect meaning positive and negative shocks do have the same effect on volatility of crude oil markets, which is consistent with the findings of Cheong (2009). This study rejects the null hypothesis of $\theta = 1$ in CBNR and WTIR and accepts the null hypothesis of $\theta = 2$. It means that the crude oil markets are better modeled by the conditional variance as compared to the conditional standard deviation models and is consistent

According to the APARCH (1, 1) model, the volatility of both NERR and RERR is asymmetric as indicated by the value ofγ, which is negative and significant. The value of the power term θ is also significant as it is greater than zero for both the NERR and RERR. It means that NERR and RERR are better modeled by conditional standard deviation model as compared to the conditional variance models. The results of the diagnostics show that there is no serial correlation up to 10 lags. The ARCH-LM test does not support the existence of any remaining ARCH effect. In case of MMR and TBR, the conditional variance process is explosive because the value of $\alpha_1 + \beta_1$ is greater than one.

Table 11: Results for the APARCH (1, 1) Model

Variables	CBNR	WTIR	NERR	RERR	MMR	TBR
Model	APARCH(1, 1)	APARCH(1, 1)	APARCH(1, 1)	APARCH(1, 1)	APARCH(1, 1)	APARCH(1, 1)
Mean Equation						
C	0.0029 (0.556)	0.0039 (0.398)	0.0046*** (0.000)	0.0097*** (0.000)	0.0021 (0.776)	0.0010** (0.0674)
AR	0.1857*** (0.006)	0.2199*** (0.001)	0.9204*** (0.000)	0.0438* (0.085)	0.2698** (0.023)	0.3041*** (0.000)
MA	-0.1657*** (0.003)	-0.1291*** (0.019)	-0.9677*** (0.000)		-0.6522*** (0.000)	0.2375*** (0.000)
Variance equation						
Ω	0.0037 (0.629)	0.0046 (0.688)	0.0342 (0.157)	0.0686* (0.091)	0.0119 (0.828)	0.0006 (0.663)
α_1	0.2411*** (0.002)	0.2187*** (0.002)	0.1475*** (0.000)	0.2710*** (0.000)	0.6684*** (0.000)	0.2553*** (0.000)
β_1	0.5804*** (0.000)	0.5657*** (0.000)	0.4927*** (0.000)	0.5759*** (0.000)	0.5459*** (0.000)	0.9487*** (0.000)
$\alpha_1 + \beta_1$	0.821	0.786	0.6403	0.847	1.214	1.204
Γ	0.1639 (0.306)	0.2887 (0.207)	-0.9981*** (0.000)	-0.2397*** (0.000)	-0.1359*** (0.014)	-0.2922*** (0.035)
θ	1.6732** (0.027)	1.5551* (0.092)	0.6252*** (0.000)	0.2723* (0.070)	2.3745*** (0.000)	0.7589*** (0.000)
Log Likelihood	335.2074	370.0466	865.0062	844.9194	950.4207	939.3921
Akaike Criteria	-2.0323	-2.2487	-5.3899	-5.2534	-5.8535	-7.5112

Note: *** denotes the significance at the 1% level, ** denotes the significance at the 5% level, and * denotes the significance at the 10% level.

Out-of-sample Forecasting Evaluation

Root mean error square (RMSE) is used as a forecasting criterion. According to the results given in Table 12, from linear models, the SES model out forms for NERR and RERR. For remaining series RW model generally appears to better as compared to other linear models. Specifically, we find that for MMR, both RW and AR models forecasted equally well. Similarly, for CBNR, both RW and MA models appear to do better forecasting as compared to other linear models. Yet, in case of TBR, RW out forms all other linear models. Finally, for WTIR, the value of RMSE is lowest in case of RW model as compared to other models.

The out-of-sample forecasting results for the non-linear models show that both GARCH (1, 1) and GARCH-M (1, 1) forecasted equally well in forecasting NERR. For RERR, GARCH (1, 1), EGARCH (1, 1), and APARCH (1, 1) forecasted equally well and appeared better than MARCH-M (1, 1) model. EGARCH (1, 1) forecasted well both for the CBNR and WTIR, as compared to other applied GARCH family models.

The comparison of linear and non-linear models shows that SES forecasted well both for the NERR and RERR. Therefore, we concluded that for NERR and RERR, linear models forecasted well as compared to the non-linear models. For MMR and TBR, again linear models forecasted well as compared to nonlinear models. However, for CBNR and WTIR, non-linear models forecasted well as compared to liner models.

Table 12. Out-of-Sample Forecasting Evaluation

	Model	Criteria	CBNR	WTIR	NERR	RERR	MMR	TBR
Linear Models	**RW**	RMSE	0.0529	0.0529	0.0132	0.0213	0.0054	0.0036
	AR	RMSE	0.0530	0.0531	0.0117	0.0178	0.0054	0.0037
	MA	RMSE	0.0529	0.0532	0.0116	0.0178	0.0055	0.0037
	SES	RMSE	0.0622	0.0554	0.0114	0.0177	0.0056	0.0037
	DES	RMSE	0.0572	0.0589	0.0177	0.0188	0.0058	0.0038
Nonlinear Models	**GARCH (1, 1)**	RMSE	0.0544	0.0522	0.0117	0.0178	0.0054	0.0038
	GARCH-M (1, 1)	RMSE	0.0536	0.0524	0.0117	0.0179	0.0057	0.0037
	EGARCH (1, 1)	RMSE	0.0733	0.0620	0.0118	0.0178	0.0053	0.0039
	APARCH (1, 1)	RMSE	0.0533	0.0521	0.0120	0.0178	0.0053	0.0040

5. Conclusion

The purpose of this study is to model and forecast volatility of Brent and West Texas Intermediate crude oil prices, nominal and real exchange rate, and money market rate and Treasury bill rate in the context of Pakistan. For this purpose, five linear and four non-linear models are used. The estimation period is January 1985 to December 2013. The in-sample estimation results show that the asymmetric GARCH family models well captured the volatility dynamics as compared to the symmetric GARCH models. This implies that volatility increases more as a result of bad news than the good news. The APARCH (1, 1) model also supports the presence of leverage effect in NERR and RERR.

The results also support that there is high persistence in the NERR and RERR. We show that in case of both CBNR and WTIR, the persistence is not much high, implying that the effect of shocks to volatility dies out with the passage of time. The out-of-sample forecasting results show that linear models outperform as compare to the nonlinear models. However, asymmetric GARCH family models outperform for capturing the volatility dynamics of the oil prices, exchange rates, and interest rates in Pakistan.

The important implication of modeling and forecasting oil price, exchange rate, and interest rate volatility is that forecasting acts as an early warning system to tackle the upcoming economic crisis. As a result, policy makers make changes and implement proper policies for handling the future economic crisis. Investors can price, hedge, and speculate well in the markets of oil, exchange rate, and interest rate by using the important information about the volatility dynamics.

References

Abdalla, S. Z. S. (2012). Modelling Exchange Rate Volatility Using GARCH Models: Empirical Evidence from Arab Countries. *International Journal of Economics and Finance, 4*(3), 216-229.

Akincilar, A., Temiz, İ., &Şahin, E. (2011).An Application of Exchange Rate Forecasting in Turkey.*Gazi University Journal of Science, 24*(4), 817-828.

Andersen, T. G., Bollerslev, T., & Meddahi, N. (2004).Analytical Evaluation of Volatility Forecasts.*International Economic Review, 45*(4), 1079-1110.

Bala, D. A., &Asemota, J. O. (2013). Exchange–Rates Volatility in Nigeria: Application of GARCH Models with Exogenous Break. *Journal of Applied Statistics, 4*(1), 89-116.

Balaban, E. (2004).Comparative Forecasting Performance of Symmetric and Asymmetric Conditional Volatility Models of an Exchange Rate.*Economics Letters, 83*(1), 99-105.

Bali, T. G. (2000). Testing the Empirical Performance of Stochastic Volatility Models of the Short-Term Interest Rate. *Journal of Financial and Quantitative Analysis, 35*(2), 191-215.

Batty, M. (1969). Monitoring an Exponential Smoothing Forecasting System. *Operational Research, 20*(3), 319-325.

Bayracı, S., & Unal, G. (2014).Stochastic Interest Rate Volatility Modeling with a Continuous-Time GARCH (1,1) Model.*Journal of Computational and Applied Mathematics, 259*(1), 464-473.

Beg, A. R. A., & Anwar, S. (2014). Detecting Volatility Persistence in GARCH Models in the Presence of the Leverage Effect. *Quantitative Finance,* 14(12),2205-2213.

Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics, 31*(3), 307-327.

Brooks, C., & Burke, S. P. (1998). Forecasting Exchange Rate Volatility Using Conditional Variance Models Selected by Information Criteria. *Economics Letters, 61*(3), 273-278.

Bruni, F. (1983). Interest and Exchange Rate Volatility: Implications for Bank Management. *GiornaledegliEconomisti e Annali di Economia, 42*(7/2), 431-458.

Chang, K.-L. (2012). Volatility Regimes, Asymmetric Basis Effects and Forecasting Performance: An Empirical Investigation of the WTI Crude Oil Futures Market. *Energy Economics, 34*(1), 294-306.

Chatfield, C., Koehler, A. B., Ord, J. K., & Snyder, R. D. (2001). A New Look at Models for Exponential Smoothing. *Journal of the Royal Statistical Society, 50*(2), 147-159.

Cheong, C. W. (2009). Modelling and Forecasting Crude Oil Markets using ARCH Type Models. *Energy Policy, 37*(6), 2346-2355.

Chong, C. W., Chun, L. S., & Ahmad, M. I. (2001). Modeling the Volatility of Currency Exchange Rate using GARCH Model. *Pertanika Journal of Social Sciences & Humanities, 10*(2), 85-95.

Covarrubias, G., Ewing, B. T., Hein, S. E., & Thompson, M. A. (2006). Modeling Volatility Changes in the 10-Year Treasury. *Physica A: Statistical Mechanics and its Applications, 369*(2), 737-744.

Dayioglu, T. (2012). Forecasting Overnight Interest Rates Volatility with Asymmetric GARCH Models. *Journal of Applied Finance & Banking, 2*(6), 151-162.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the Estimators for Autoregressive Time Series with a Unit Root. *Journal of the American statistical association, 74*(366a), 427-431.

Ding, Z., Granger, C. W., & Engle, R. F. (1993). A Long Memory Property of Stock Market Returns and a New Model. *Journal of Empirical Finance, 1*(1), 83-106.

Edwards, S., & Susmel, R. (2003).Interest-Rate Volatility in Emerging Markets. *Review of Economics and Statistics, 85*(2), 328-348.

Engle, R. (2001). GARCH 101: The Use of ARCH/GARCH Models in Applied Econometrics. *Journal of Economic Perspectives, 15*(4), 157-168.

Engle, R. F. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation.*Econometrica, 50*(4), 987-1007.

Engle, R. F., & Bollerslev, T. (1986). Modelling the Persistence of Conditional Variances. *Econometric Reviews, 5*(1), 1-50.

Engle, R. F., Lilien, D. M., & Robins, R. P. (1987). Estimating Time Varying Risk Premia in the Term Structure: The ARCH-M Model. *Econometrica, 55*(2), 391-407.

Geman, H. (2007). Mean Reversion Versus Random Walk in Oil and Natural Gas Prices. *Advances in Mathematical Finance,* 219-228.

Hassan, M. (2013). Volatility of Exchange Rate Effecting Trade Growth-A Case of Pakistan with US, UK and UAE.*European Scientific Journal, 9*(22), 227-288.

Hassan, S. A. (2011). Modeling Asymmetric Volatility in Oil Prices. *Journal of Applied Business Research (JABR), 27*(3), 71-78.

Hegerty, S. W. (2014). Interest-Rate Volatility and Volatility Transmission in Nine Latin American Countries. *Applied Financial Economics, 24*(13), 927-937.

Hou, A., & Suardi, S. (2012). A Nonparametric GARCH Model of Crude Oil Price Return Volatility. *Energy Economics, 34*(2), 618-626.

Hsieh, D. A. (1989). Modeling Heteroscedasticity in Daily Foreign-Exchange Rates. Journal of Business & Economic Statistics, 7(3), 307-317.

Irfan, M., & Awais, M. (2010).Modelling Volatility of Short Term Interest Rates by ARCH Family Model: Evidence from Pakistan and India. *World Applied Sciences Journal, 9*(10), 1089-1094.

Kang, S. H., Kang, S.-M., & Yoon, S.-M. (2009). Forecasting Volatility of Crude Oil Markets. *Energy Economics, 31*(1), 119-125.

Kamal, Y., Haq, H., Ghani, U., & Khan, M. (2012). Modeling the Exchange Rate Volatility, using Generalized Autoregressive Conditionally Heteroscedastic (GARCH) Type Models: Evidence from Pakistan. *African Journal of Business Management, 6*(8), 2830-2838.

Khan, A. J. (2013). One-Step-Ahead Forecastability of GARCH (1, 1): A Comparative Analysis of USD- and PKR-Based Exchange Rate Volatilities Abdul Jalil Khan and Parvez Azim. *Lahore Journal of Economics, 18*(1), 1-38.

Khan, F., & Asghar, Z. (2010). Modeling and Volatility Analysis of Oil Companies in Pakistan. *Interstat, 1*(1), 1-21.

Koutmos, G. (2012). Modeling Interest Rate Volatility: An Extended EGARCH Approach. *Managerial Finance, 38*(6), 628-635.

Liew, V. (2004).On Autoregressive Order Selection Criteria. *Universiti Putra Malysia, 1*(12), 1-14.

Liu, L., & Wan, J. (2012). A study of Shanghai fuel oil futures price volatility based on high frequency data: Long-range dependence, modeling and forecasting. *Economic Modelling, 29*(6), 2245-2253.

MacDonald, G. M., & MacKinnon, J. G. (1985). Convenient Methods for Estimation of Linear Regression Models with MA (1) Errors. *Canadian Journal of Economics, 18*(1), 106-116.

Malik, K. S. (2011). Exchange Rate Forecasting and Model Selection in Pakistan (2000-2010). *Journal of Business & Economics, 3*(1), 77-101.

McKenzie, M. D. (1997). ARCH Modeling of Australian Bilateral Exchange Rate Data. *Applied Financial Economics, 7*(2), 147-164.

Mohammadi, H., & Su, L. (2010). International evidence on crude oil price dynamics: Applications of ARIMA-GARCH models. *Energy Economics, 32*(5), 1001-1008.

Moshiri, S., & Foroutan, F. (2006). Forecasting Nonlinear Crude Oil Futures Prices. *The Energy Journal, 27*(4), 81-95.

Mudakkar, S. R., Uppal, J. Y., Zaman, K., Naseem, I., & Shah, G. U. D. (2013). Foreign Exchange Risk in a Managed Float Regime: A Case Study of Pakistani Rupee. *Economic Modelling, 35*(51), 409-417.

Musa, Y., Tasi'u, M., & Bello, A. (2014). Forecasting of Exchange Rate Volatility between Naira and US Dollar Using GARCH Models. *International Journal of Academic Research in Business and Social Sciences, 4*(7), 369-381.

Narayan, P. K., & Narayan, S. (2007). Modelling Oil Price Volatility. *Energy Policy, 35*(12), 6549-6553.

Nelson, D. B. (1991). Conditional Heteroskedasticity in Asset Returns: A New Approach. *Econometrica: Journal of the Econometric Society, 59*(2), 347-370.

Ng, S., & Perron, P. (2001). Lag Length Selection and the Construction of Unit Root Tests with Good Size and Power. *Econometrica, 69*(6), 1519-1554.

Olowe, R. A. (2009). Stock return, volatility and the global financial crisis in an emerging market: The Nigerian case. *International Review of Business Research Papers, 5*(4), 426-447.

Pasha, G., Qasim, T., & Aslam, M. (2007). Estimating and Forecasting Volatility of Financial Time Series in Pakistan with GARCH-Type Models. *The Lahore Journal of Economics, 12*(2), 115-149.

Poon, S.-H., & Granger, C. W. (2003). Forecasting Volatility in Financial Markets: A Review. *Journal of Economic Literature, 41*(2), 478-539.

Ramzan, S., Ramzan, S., & Zahid, F. M. (2012).Modeling and Forecasting Exchange Rate Dynamics in Pakistan Using ARCH Family of Models. *Electronic Journal of Applied Statistical Analysis, 5*(1), 15-29.

Robinson, R. I. (1954). Forecasting Interest Rates. *The Journal of Business, 27*(1), 87-100.

Salisu, A. A., & Fasanya, I. O. (2012).Comparative Performance of Volatility Models for Oil Price. *International Journal of Energy Economics and Policy, 2*(3), 167-183.

Shah, M. K. A., Hyder, Z., & Pervaiz, M. K. (2009). Central Bank Intervention and Exchange Rate Volatility in Pakistan: An Analysis using GARCH-X model. *Applied Financial Economics, 19*(18), 1497-1508.

Taylor, J. W. (2003). Short-Term Electricity Demand Forecasting using Double Seasonal Exponential Smoothing. *Journal of the Operational Research Society, 54*(8), 799-805.

Wang, Y., Wu, C., & Wei, Y. (2011). Can GARCH-Class Models Capture Long Memory in WTI Crude Oil Markets? *Economic Modelling, 28*(3), 921-927.

Wei, Y., Wang, Y., & Huang, D. (2010). Forecasting Crude Oil Market Volatility: Further Evidence using GARCH-Class Models. *Energy Economics, 32*(6), 1477-1484.

Zahangir Alam, M. (2012). Forecasting the BDT/USD Exchange Rate using Autoregressive Model. *Global Journal of Management And Business Research, 12*(19).

Zakaria, M., Ahmad, E., & Iqbal, M. M. (2007). Nominal Exchange Rate Variability: A Case Study of Pakistan. *Journal of Economic Cooperation, 28*(1), 73-98.

Zou, L., Rose, L. C., & Pinfold, J. F. (2007). Asymmetric Information Impacts: Evidence from the Australian Treasury-Bond Futures Market. *Pacific Economic Review, 12*(5), 665-681.

Appendix

Table A1: ARCH Effect Diagnostics

	ARCH effect			Q-statistics for returns				Q-statistics for squared returns			
	ARCH(2)	ARCH(5)	ARCH(10)	Q(5)	Q(10)	Q(20)	Q(50)	Q(5)	Q(10)	Q(20)	Q(50)
NERR	2.2834*** (0.010)	5.9365*** (0.000)	3.2248*** (0.001)	15.4806*** (0.008)	17.1296*** (0.072)	36.3825*** (0.012)	90.2664*** (0.004)	28.2870*** (0.000)	29.5801*** (0.001)	39.1787*** (0.006)	94.7385*** (0.000)
RERR	1.3780** (0.002)	4.2828*** (0.001)	2.4167*** (0.001)	30.6440*** (0.000)	32.4190*** (0.000)	51.0678*** (0.000)	93.8506*** (0.000)	21.9391*** (0.000)	23.7012*** (0.000)	31.0840*** (0.000)	75.2271*** (0.000)
MMR	23.392*** (0.000)	14.377*** (0.000)	8.4892*** (0.000)	78.9983*** (0.000)	106.251*** (0.000)	135.270*** (0.000)	241.871*** (0.000)	119.125*** (0.000)	209.517*** (0.000)	294.691*** (0.000)	383.117*** (0.000)
TBR	152.90*** (0.000)	63.563*** (0.000)	30.770*** (0.000)	422.789*** (0.000)	435.830*** (0.000)	438.135*** (0.000)	559.452*** (0.000)	199.797*** (0.000)	201.405*** (0.000)	241.629*** (0.000)	357.271*** (0.000)
CBNR	25.023*** (0.000)	10.724*** (0.000)	6.8248*** (0.000)	10.0303* (0.074)	23.3888*** (0.009)	40.9758*** (0.004)	91.4194*** (0.000)	58.2099*** (0.000)	70.7970 (0.000)	78.7536*** (0.000)	99.3172*** (0.000)
WTIR	33.865*** (0.000)	15.013*** (0.000)	7.8626*** (0.000)	21.1544*** (0.001)	33.4364*** (0.000)	49.5932*** (0.000)	83.3419*** (0.002)	91.3332*** (0.000)	101.133*** (0.000)	104.470*** (0.000)	110.493*** (0.000)

Note: *** shows the 1% significance level, ** shows the 5% significance level, and * shows the 10% significance level. P-values are given in brackets. Q-statistics is the Ljung-Box statistics based on standardized residuals and square of standardized residuals up to lag 50 with H_0: no serial correlation. Lagrange multiplier test is used for ARCH effect up to order n and its H_0: there is no ARCH effect.

TableA2: Diagnostic Tests for the GARCH (1, 1) Model

	CBNR	WTIR	NERR	RERR	MMR	TBR
Normality Test						
Skewness	-0.4279	-0.1717	3.4601	2.8679	0.2007	0.3852
Excess kurt	5.0586	3.4857	19.241	15.9414	4.4225	6.7586
Jarque-Bera	66.6886 (0.000)	4.7496 (0.093)	4142.359 (0.000)	2688.444 (0.000)	29.3124 (0.000)	152.1188 (0.000)
Q-statistics on standardized residuals						
Q(5)	1.6740 (0.643)	3.4811 (0.323)	8.5403 (0.074)	9.4940 (0.150)	4.4645 (0.215)	5.8609 (0.119)
Q(10)	7.0117 (0.535)	5.5289 (0.700)	10.485 (0.313)	12.655 (0.179)	11.506 (0.175)	11.483 (0.176)
Q(20)	25.242 (0.118)	21.808 (0.122)	27.337 (0.097)	32.010 (0.031)**	25.938 (0.101)	16.973 (0.525)
Q(50)	66.759 (0.038)	60.928 (0.100)	61.676 (0.106)	78.069*** (0.005)	65.696** (0.046)	43.721 (0.649)
Q-statistics on squared standardized residuals						
Q(5)	1.6993 (0.889)	4.2096 (0.520)	3.7343 (0.588)	7.9656 (0.158)	11.331 (0.145)	2.3907 (0.792)
Q(10)	3.2548 (0.975)	5.7168 (0.838)	5.7167 (0.838)	9.2312 (0.510)	12.837 (0.233)	6.2718 (0.792)
Q(20)	6.6916 (0.998)	9.5933 (0.975)	15.181 (0.766)	21.660 (0.359)	23.185 (0.280)	10.493 (0.958)
Q(50)	20.567 (1.000)	30.683 (0.986)	72.842 (0.019)	72.591 (0.020)	55.996 (0.260)	42.714 (0.758)
ARCH-Test						
ARCH(2)	0.2473 (0.781)	0.0489 (0.952)	0.0383 (0.962)	0.1553 (0.856)	3.1153 (0.145)	0.1758 (0.838)
ARCH(5)	0.3396 (0.889)	0.8644 (0.505)	0.7167 (0.611)	1.5358 (0.178)	2.0404 (0.172)	0.4640 (0.802)
ARCH(10)	0.3034 (0.980)	0.5856 (0.8255)	0.5228 (0.873)	0.8613 (0.570)	0.9704 (0.469)	0.5680 (0.839)

Note: *** denotes the significance at the 1% level, ** denotes the significance at the 5% level, and * denotes the significance at the 10% level.

Table A3: Diagnostic Tests for the GARCH-M (1, 1) Model

	CBNR	WTIR	NERR	RERR	MMR	TBR
Normality Test						
Skewness	-0.4332	-0.1692	3.656	2.9020	0.2067	0.4116
Excess kurt	5.0691	3.4973	19.971	16.2973	4.2124	6.8517
Jarque-Bera	67.470 (0.000)	4.8564 (0.088)	6087.4 (0.000)	2824.317 (0.000)	22.0182 (0.000)	160.3103 (0.000)
Q- statistics on standardized residuals						
Q(5)	1.6649 (0.645)	3.4185 (0.331)	12.515 (0.114)	11.163 (0.125)	3.9537 (0.267)	5.4537 (0.141)
Q(10)	7.0107 (0.535)	5.3443 (0.720)	13.319 (0.149)	14.736 (0.198)	10.012 (0.264)	11.478 (0.176)
Q(20)	25.607 (0.109)	25.295 (0.117)	21.319 (0.319)	33.147 (0.123)**	25.201 (0.119)	17.080 (0.518)
Q(50)	67.411 (0.034)**	61.629 (0.089)*	60.542 (0.125)	77.796 (0.005)***	61.460 (0.092)*	49.010 (0.432)
Q- statistics on squared standardized residuals						
Q(5)	1.7059 (0.888)	4.1194 (0.532)	0.5065 (0.992)	9.2450 (0.100)	9.3643 (0.195)	1.8823 (0.865)
Q(10)	3.0730 (0.980)	5.7563 (0.835)	1.3276 (0.999)	10.382 (0.408)	10.739 (0.378)	5.1335 (0.882)
Q(20)	6.3236 (0.988)	9.5610 (0.975)	8.0579 (0.991)	22.649 (0.306)	25.746 (0.174)	10.417 (0.960)
Q(50)	19.220 (1.000)	29.294 (0.991)	80.184*** (0.004)	74.264*** (0.015)	59.098 (0.177)	44.479 (0.694)
ARCH-Test						
ARCH(2)	0.2013 (0.817)	0.0830 (0.920)	0.0060 (0.993)	0.1549 (0.856)	1.3445 (0.262)	0.0966 (0.907)
ARCH(5)	0.3409 (0.887)	0.8437 (0.519)	0.0951 (0.993)	1.7773 (0.117)	1.6757 (0.140)	0.3752 (0.865)
ARCH(10)	0.2850 (0.984)	0.5949 (0.817)	0.1258 (0.999)	0.9740 (0.466)	0.8450 (0.585)	0.4591 (0.914)

Note: *** denotes the significance at the 1% level, ** denotes the significance at the 5% level, and * denotes the significance at the 10% level.

Table A4: Diagnostic Tests for the EGARCH (1, 1) Model

	NERR	RERR	MMR	TBR	CBNR	WTIR
Normality Test						
Skewness	3.7097	2.9792	0.1964	0.2108	-0.3721	-0.1085
Excess kurt	23.723	17.2908	4.7473	7.2395	4.9146	3.4796
Jarque-Bera	6439.789 (0.000)	3216.396 (0.000)	43.0349 (0.000)	187.5698 (0.000)	56.6127 (0.000)	3.7190 (0.156)
Q- statistics on standardized residuals						
Q(5)	2.5229 (0.471)	10.521 (0.133)	8.4894 (0.137)	6.2913 (0.177)	1.8990 (0.594)	3.5173 (0.319)
Q(10)	6.4964 (0.592)	133.139 (0.156)	16.779 (0.132)	13.827* (0.086)	6.6036 (0.580)	4.6885 (0.790)
Q(20)	24.222 (0.148)	32.384 (0.028)**	32.048 (0.122)	19.390 (0.368)	24.230 (0.148)	22.892 (0.195)
Q(50)	70.517 (0.019)***	79.959 (0.003)***	76.358** (0.026)	49.223 (0.424)	62.632 (0.076)*	57.347 (0.167)
Q- statistics on squared standardized residuals						
Q(5)	8.63655 (0.125)	11.199 (0.148)	9.0720 (0.106)	2.3974 (0.792)	2.4118 (0.790)	3.7065 (0.592)
Q(10)	9.0101 (0.513)	12.180 (0.273)	11.685 (0.307)	7.1917 (0.707)	3.8082 (0.956)	4.9302 (0.896)
Q(20)	24.649 (0.215)	26.454 (0.151)	25.888 (0.170)	12.522 (0.897)	7.4892 (0.995)	8.2420 (0.990)
Q(50)	96.266*** (0.000)	76.521*** (0.009)	59.209 (0.175)	43.558 (0.725)	22.511 (1.00)	28.925 (0.993)
ARCH-Test						
ARCH(2)	0.0462 (0.955)	0.1411 (0.868)	0.9728 (0.379)	0.1773 (0.837)	0.6722 (0.511)	0.1272 (0.880)
ARCH(5)	1.6789 (0.139)	2.1782 (0.156)	1.6382 (0.149)	0.4540 (0.810)	0.4613 (0.804)	0.7568 (0.582)
ARCH(10)	0.8475 (0.583)	1.1701 (0.311)	0.8184 (0.611)	0.6613 (0.759)	0.3615 (0.962)	0.5057 (0.885)

Note: *** denotes the significance at the 1% level, ** denotes the significance at the 5% level, and * denotes the significance at the 10% level.

A5: Diagnostic Tests for the APARCH (1, 1) Model						
	CBNR	WTIR	NERR	RERR	MMR	TBR
Normality Test						
Skewness	-0.3546	-0.0984	4.4118	2.4570	0.2265	0.2409
Excess kurt	5.0856	3.5164	28.928	13.816	4.1921	7.2593
Jarque-Bera	65.1118 (0.000)	4.0992 (0.1287)	9938.794 (0.000)	1876.197 (0.000)	21.8210 (0.000)	189.8646 (0.000)
Q- statistics on standardized residuals						
Q(5)	1.8172 (0.611)	3.3750 (0.337)	17.208 (0.114)	15.634 (0.004)	4.1366 (0.247)	6.8642 (0.177)
Q(10)	6.7832 (0.560)	4.7001 (0.789)	19.215 (0.134)	18.754 (0.127)	11.750 (0.163)	13.744* (0.089)
Q(20)	25.277 (0.117)	23.982 (0.156)	41.498*** (0.001)	42.089*** (0.002)	25.231 (0.119)	19.081 (0.387)
Q(50)	64.931 (0.052)	58.878 (0.135)	102.61*** (0.000)	94.704*** (0.000)	66.787** (0.038)	50.408 (0.378)
Q- statistics on squared standardized residuals						
Q(5)	1.4278 (0.921)	3.0961 (0.685)	20.190 (0.115)	10.339 (0.166)	11.022 (0.151)	2.0111 (0.848)
Q(10)	2.5776 (0.990)	4.1687 (0.939)	15.100 (0.128)	11.743 (0.303)	12.049 (0.282)	7.1451 (0.712)
Q(20)	5.8798 (0.999)	7.3722 (0.995)	38.918*** (0.007)	31.355** (0.051)	23.300 (0.274)	12.337 (0.904)
Q(50)	19.809 (1.000)	27.537 (0.996)	89.479*** (0.001)	78.298*** (0.006)	57.229 (0.225)	44.017 (0.711)
ARCH-Test						
ARCH(2)	0.1846 (0.832)	0.1616 (0.984)	0.1612 (0.851)	0.4230 (0.655)	3.0422 (0.149)	0.1735 (0.841)
ARCH(5)	0.2837 (0.906)	0.6238 (0.682)	4.0146 (0.510)	1.9349* (0.088)	1.9545* (0.085)	0.3816 (0.861)
ARCH(10)	0.2365 (0.992)	0.4185 (0.937)	2.0854** (0.026)	1.0397 (0.409)	0.9218 (0.513)	0.6489 (0.771)

Note: *** denotes the significance at the 1% level, ** denotes the significance at the 5% level, and * denotes the significance at the 10% level.