IJMIR (ISSN 2320 – 1177) Volume 6 Issue 2 December 2017

Modeling India-US Exchange Rate Volatility Using GARCH Models

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Abstract

To understand the market expectations and uncertainty, study of foreign exchange volatility is very important. It is matter of interest to researchers as well as policy makers as it helps us to measure the impact on asset prices. In this work, we have examined the Indian exchange rate volatility against US dollar, using daily data for the period January 2010 to September 2015. Our modeling framework is based on the Generalized Autoregressive Conditional Heteroskedastic (GARCH) models. We have observed strong evidence of conditional shocks and their asymmetric and transitory impact on exchange rate volatility.

Keywords: *Exchange Rate, ARCH, GARCH, Volatility*, *Asymmetric Effects*.

Introduction

Financial volatility has significant influence on the economy growth and the policy decision makers depend heavily upon the volatility modeling anticipation on the vulnerabilities of financial markets and economy (Poon and Granger (2003). An investor's confidence to invest in particular country is significantly related to high volatilities in exchange rate. This is one the basic reason why volatility models are used to explain the enduring and significant instance in the foreign exchange rate movements (Kamal et al., 2012).

The traditional measure of volatility as represented by variance and standard deviation is unconditional and does not recognize interesting patterns in asset volatility, e.g., time-varying and clustering properties (Olowe, 2009). Researchers have introduced various models to be able to explain and predict these patterns in volatility. One such approach is represented by time-varying volatility models which were expressed by Engle (1982) as autoregressive conditional heteroscedasticity (ARCH) model and extended by Bollerslev (1986) into generalized ARCH (GARCH) model. These models recognize the difference between the conditional and the unconditional volatility of stochastic process, where the former varies over time, while the latter remains constant (McMillan and Thupayagale 2010).

In this article, drawing on the literature (see, inter alia, Brooks, 2001; Taylor and Sarno, 2004; Sanro, et al., 2005; Narayan and Narayan, 2007a; Taylor, 2006) that have found exchange rates to display nonlinear behaviour and the subsequent literature (see, inter alia, Herwartz and Reimers, 2002; Tsui and Ho, 2004; and Kim and Sheen, 2006) on exchange rate volatility, Generally, this literature has found that shocks have a persistent impact on exchange rate.

Volatility in exchange rates volatility in India has a big concern is not only due to the rupee depreciation but also rupee appreciation that is causing concern to understand the economic disparity of the country. Ahmed and Suliman (2011) pointed out the importance of currency exchange rate volatility because of its economic and financial applications like portfolio optimization, risk management, etc.

Data and Research Methodology

The time series data for rupee exchange rate against US dollar is used for modeling volatility. The daily rupee exchange rate against US dollar for the period January 4, 2010 to September 30, 2015 is used to estimate the volatility, excluding public holidays. These data series have been obtained from one of the most reliable, i.e., IMF online database. In this study, daily returns are the first difference in logarithm of closing prices of rupee exchange rate of successive days. With the given data set, fluctuations in exchange returns reflect volatility in stock market. Suppose E_t the exchange rate at time period t, E_{t-1} is the exchange rate in the preceding time period $t-1$ the rate of return R_t in 't' time period would be as follows:

$$R_t = Ln(E_t) - Ln(E_{t-1})$$

Generally return consists of two components; expected return $E(R_t)$ (due to economic fundamentals) and unexpected return 'ε_t' (due to good or bad news). Symbolically, it can be written as follows:

$$R_t = E(R_t) + \varepsilon_t$$

An increase in unexpected rise in return) advocates the arrival of good news; on the contrary, a downturn in εt unexpected decline in return is a mark of bad news. Volatility in forex market as a result of expected variations in exchange returns is termed as expected volatility, while volatility resultant to unexpected variations in exchange range rate returns is known as unexpected volatility. In modeling such situations, autoregressive conditional heteroskedasticity (ARCH) approach is applied wherein the conditional variance is used as a function of past error term and allows the variance of error term to vary over time (Engle, 1982). It implies that volatility can be forecasted by inclusion of the past news as a function of conditional variance. This process is called autoregressive conditional heteroskedasticity.

ARCH Model

Before the ARCH model introduced by Engle (1982), the most common way to forecast volatility was to determine volatility using a number of past observations under the assumption of homoscedasticity. However, variance is not constant. Hence, it was inefficient to give same weight to every observation considering that the recent observations are more important. ARCH model, on the other hand, assumes that variance is not constant and it estimates the weight parameters and it becomes easier to forecast variance by using the most suitable weights. Mean function of ARCH(1) is a simple first order auto regression:

$$R_t = c + \beta R_{t-1} + \varepsilon_t$$

and the conditional variance equation is as follows:

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2$$

GARCH Model

The GARCH model was developed by Bollerslev (1986) and Taylor (1986) independently. In GARCH(1,1) model, conditional variance depends on previous own lag. Mean equation of GARCH(1,1):

$$R_t = c + \beta R_{t-1} + \varepsilon_t$$

and the variance equation is:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$$

Where ω is constant, ε_{t-1}^2 is the ARCH term and σ_{t-1}^2 is the GARCH term. As we can see, today's volatility is a function of yesterday's volatility and yesterday's squared error.

The GJR-GARCH Model – GJR-GARCH (1,1)

This model is proposed by Glosten, Jagannathan and Runkle (1993). Conditional variance is given by;

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma\varepsilon_{t-1}^2 I_{t-1}$$

Where $I_{t-1} = 1$ if $\varepsilon_{t-1} < 0$ and $I_{t-1} = 0$ otherwise.

The Exponential GARCH Model - EGARCH

Nelson's (1991) EGARCH(1,1) model's variance equation is as follows:

$$\log(\sigma_t^2) = \omega + \alpha(\frac{\varepsilon_{t-1}}{\sigma_{t-1}}) + \beta\left[(\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}}) - \sqrt{\frac{2}{\pi}}\right] + \gamma\log(\sigma_{t-1}^2)$$

Results and Discussion

The descriptive statistics of the return on rupee value and its first log difference against US dollar (RD, LRD) are depicted in Table 1. In a standard normal distribution, kurtosis is 3. A value lesser or greater than 3 kurtosis coefficients indicates flatness and peakedness of the data series. The higher value of kurtosis shows that the data series is peaked, moreover data series is highly peaked with kurtosis 8.56 as compared to normal distribution. Table 1 also shows that the Jarque-Bera (JB) test of normality for all the data series rejects the null hypothesis of normality at 1% significant level.

Testing for Stationarity of the Series

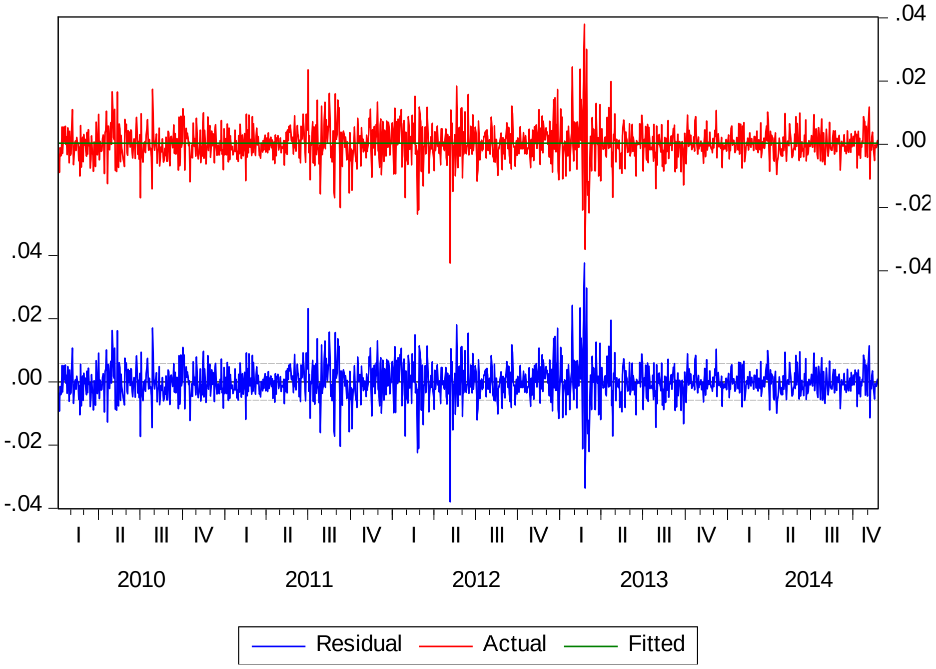
To examine whether the daily exchange rate against US Dollar and their first log difference are stationary series, the Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979), Philips-Perron (PP) test have been applied to confirm the results about the stationarity of the series. The results of the unit root test are shown in Table 2 and 3. The ADF and PP test statistics are significant at 1% level, thus rejecting the null hypothesis of the presence of unit root in the data.

Table 1: Unit root test of the daily return								
	Augmented Dickey-Fuller test				Phillips-Perron test			
	Statistic	Critical values			Statistic	Critical values		
		1% level	5% level	10% level		1% level	5% level	10% level
Exchange Rate Return	-27.99 (0.00)	-3.43	-2.86	-2.56	-36.74 (0.00)	-3.43	-2.86	-2.56

Testing for Heteroskedasticity

We cannot use homoscedastic model to estimate volatility. Thus, before modeling the volatility of rupee exchange log return series against major currencies, testing for the heteroskedasticity in residuals is necessary. At the beginning, we obtain the residuals from an Autoregressive and Moving Average (ARMA).

Figure 1: Log Difference of INR per US Dollar



Once the residuals from ARMA(1, 1) are obtained, the existence of heteroskedasticity in residuals of log exchange rate return series is checked using Engle's Lagrange Multiplier (LM) test for ARCH effects (Engle, 1982). This particular heteroskedasticity specification was motivated by the observation that in many financial time series, the magnitude of residuals appeared to be related to the magnitude of recent residuals (Chakrabarti and Sen, 2011). Table 3 presents the results of heteroskedasticity test LM to check for the presence of ARCH effect in the residual series at lag 1. From the table, we infer that for all the log rupee exchange return series, both *F*-statistics and LM statistics are significant at 1% level in the first lags. The zero *p*-value indicates the presence of ARCH effect. Based on these results, we reject the null hypothesis of absence of ARCH effects (homoskedasticity) in residual series of log rupee exchange return series. These results suggest that the log return series of Indian rupee-against US dollar, have the presence of ARCH. This observation directs us to estimate the exchange rate volatility using different classes of GARCH models

Table 2: Estimation Results of GARCH(p, q) Model

	GARCH (1,1)	TGARCH (1,1)	EGARCH (1,1)
Constant	5.62E-07	4.49E-07	-0.432
α	0.062*	0.073*	0.162*
β	0.921*	-0.048*	0.066*
γ		0.936*	0.970*
Residual Diagnostics: ARCH-LM Test			
***F*-Statistic**	0.39712	0.99917	0.66398
Prob. *F*(1,1272)	0.5297	0.3177	0.4143

*indicates that coefficient are significant at 1% level of significance

Table 2 shows the results of GARCH (p, q) model used for estimating the daily foreign exchange rate volatility of Indian rupee against US Dollar for the sample period ranging from January 5, 2010 to September 16, 2015. From the table we can see that all the coefficients of model against different currencies, (Constant), α *(*ARCH effect) and β *(*GARCH effect), in the sample period are statistically significant at 1% level. The lagged conditional and squared variances have impact on the volatility and it is supported by both ARCH Term (α*)* and GARCH Term *(*β*)* which is significant. The highly significant α *(*ARCH effect) in the sample period evidenced the presence of volatility clustering in GARCH (1, 1) model in the data series. It also indicates that the past squared residual term (ARCH term) is significantly affected by the volatility risk in exchange rate. The coefficient of β (GARCH effect) also shows highly statistical significance for rupee exchange rate against US Dollar. It indicates that the past volatility of Indian foreign exchange rate is significantly influencing the current rupee volatility.

The TGARCH model used to test leverage effect or asymmetry in the daily foreign exchange rate volatility of Indian rupee against US dollar in Table 2. The estimated results of coefficients in TGARCH (1, 1) model for the selected series are statistically significant at 1% and 5% levels of significance. In the case of asymmetric term or leverage effect (γ), a statistically significant value suggests that there exists the leverage effect and asymmetric behavior in daily Indian rupee exchange rate against US dollar. Further for all the selected series, the leverage effect term shows a negative sign, indicating that positive shocks (good news) have large impact on next period volatility than negative shocks (bad news) of the same sign or magnitude. All the parameters presented in the table are statistically significant at 1% and 5% levels. The significance of EGARCH term (γ) indicates the presence of asymmetric behavior of volatility of Indian rupee against US dollar. The positive coefficients of EGARCH term suggest that the positive shocks (good news) have more effect on volatility than that of negative shocks. The null hypothesis of no heteroskedasticity in the residuals is accepted in GARCH (1, 1), TGARCH (1, 1) and EGARCH (1, 1) model.

Conclusion

In this paper we have tried to explore the comparative ability of different statistical and econometric volatility forecasting models in the context of Indian rupee against US dollar. Three different models were considered in this study. The volatility of the rupee exchange rate returns has been modeled by using univariate GARCH models. The study includes both symmetric and asymmetric models that capture the most common stylized facts about currency returns such as volatility clustering and leverage effect. These models are GARCH (1, 1), TGARCH (1, 1) and EGARCH (1, 1), for log difference of rupee exchange rate return series against US dollar. GARCH (1, 1) model is used for capturing the symmetric effect, whereas the TGARCH (1, 1) and EGARCH (1, 1), models for capturing the asymmetric effect. The paper finds strong evidence that daily rupee exchange returns volatility could be characterized by the above-mentioned models. For all series, the empirical analysis was supportive of the symmetric volatility hypothesis, which means rupee exchange rate returns are volatile and that positive and negative shocks (good and bad news) of the same magnitude have the same impact and effect on the future volatility level. The parameter estimates of the GARCH (p, q) models indicate a high degree of persistence in the conditional volatility of exchange rate returns which means an explosive volatility.

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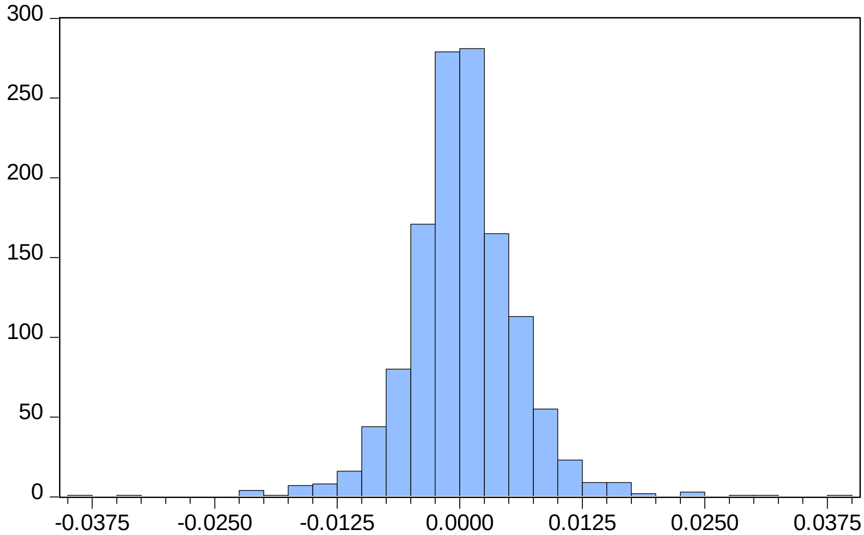
APPENDIX

Figure2: Descriptive Statistic



Series: INDIA_ER
Sample 1/05/2010 9/16/2015
Observations 1275

Mean	0.000343
Median	0.000178
Maximum	0.037919
Minimum	-0.037560
Std. Dev.	0.005809
Skewness	0.089825
Kurtosis	8.569932
Jarque-Bera	1649.872
Probability	0.000000

Table 3: Results of Unit Root Test

Null Hypothesis: INDIA_ER has a unit root
Exogenous: Constant
Bandwidth: 2 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-36.74063	0.0000
Test critical values:	1% level	-3.435271	
	5% level	-2.863601	
	10% level	-2.567917	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	3.37E-05
HAC corrected variance (Bartlett kernel)	3.16E-05

Phillips-Perron Test Equation
Dependent Variable: D(INDIA_ER)
Method: Least Squares
Date: 10/12/15 Time: 09:46
Sample (adjusted): 1/06/2010 11/24/2014
Included observations: 1274 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
INDIA_ER(-1)	-1.028128	0.028024	-36.68725	0.0000
C	0.000355	0.000163	2.180164	0.0294

R-squared	0.514124	Mean dependent var	3.44E-06
Adjusted R-squared	0.513742	S.D. dependent var	0.008332
S.E. of regression	0.005810	Akaike info criterion	-7.456878
Sum squared resid	0.042939	Schwarz criterion	-7.448794
Log likelihood	4752.031	Hannan-Quinn criter.	-7.453842
F-statistic	1345.954	Durbin-Watson stat	2.004430
Prob(F-statistic)	0.000000		

Null Hypothesis: INDIA_ER has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=22)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-27.99356	0.0000
Test critical values:	1% level	-3.435275	
	5% level	-2.863602	
	10% level	-2.567918	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(INDIA_ER)
Method: Least Squares
Date: 10/12/15 Time: 09:45
Sample (adjusted): 1/07/2010 11/24/2014
Included observations: 1273 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
INDIA_ER(-1)	-1.120691	0.040034	-27.99356	0.0000
D(INDIA_ER(-1))	0.089313	0.027916	3.199322	0.0014
C	0.000395	0.000163	2.424478	0.0155

R-squared	0.518806	Mean dependent var	8.08E-06
Adjusted R-squared	0.518048	S.D. dependent var	0.008334
S.E. of regression	0.005785	Akaike info criterion	-7.464595
Sum squared resid	0.042508	Schwarz criterion	-7.452460
Log likelihood	4754.215	Hannan-Quinn criter.	-7.460037
F-statistic	684.6328	Durbin-Watson stat	2.000217
Prob(F-statistic)	0.000000		

Table 4: Test of Hetroskedasticity to Identify Presence of ARCH

Heteroskedasticity Test: ARCH

F-statistic	176.0492	Prob. F(1,1272)	0.0000
Obs*R-squared	154.8888	Prob. Chi-Square(1)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 10/12/15 Time: 09:50
Sample (adjusted): 1/06/2010 11/24/2014
Included observations: 1274 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.20E-05	2.59E-06	8.466040	0.0000
RESID^2(-1)	0.348688	0.026280	13.26835	0.0000

R-squared	0.121577	Mean dependent var	3.37E-05
Adjusted R-squared	0.120886	S.D. dependent var	9.28E-05
S.E. of regression	8.70E-05	Akaike info criterion	-15.85893
Sum squared resid	9.64E-06	Schwarz criterion	-15.85085
Log likelihood	10104.14	Hannan-Quinn criter.	-15.85590
F-statistic	176.0492	Durbin-Watson stat	2.161976
Prob(F-statistic)	0.000000		

Table 5: Estimation of GARCH(1,1) and Residual Diagnostics(ARCH LM Test)

Dependent Variable: INDIA_ER
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 10/12/15 Time: 14:12
Sample (adjusted): 1/05/2010 11/24/2014
Included observations: 1275 after adjustments
Convergence achieved after 30 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000207	0.000144	1.439608	0.1500
		Variance Equation		
C	5.62E-07	1.64E-07	3.426960	0.0006
RESID(-1)^2	0.062072	0.006753	9.192204	0.0000
GARCH(-1)	0.921591	0.007703	119.6352	0.0000

R-squared	-0.000547	Mean dependent var	0.000343
Adjusted R-squared	-0.000547	S.D. dependent var	0.005809
S.E. of regression	0.005810	Akaike info criterion	-7.636840
Sum squared resid	0.043008	Schwarz criterion	-7.620681
Log likelihood	4872.486	Hannan-Quinn criter.	-7.630771
Durbin-Watson stat	2.054843		

Heteroskedasticity Test: ARCH

F-statistic	0.395119	Prob. F(1,1272)	0.5297
Obs*R-squared	0.395617	Prob. Chi-Square(1)	0.5294

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 10/12/15 Time: 14:17
Sample (adjusted): 1/06/2010 11/24/2014
Included observations: 1274 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.981528	0.076885	12.76624	0.0000
WGT_RESID^2(-1)	0.017622	0.028035	0.628585	0.5297

R-squared	0.000311	Mean dependent var	0.999140
Adjusted R-squared	-0.000475	S.D. dependent var	2.554934
S.E. of regression	2.555541	Akaike info criterion	4.715974
Sum squared resid	8307.166	Schwarz criterion	4.724058
Log likelihood	-3002.075	Hannan-Quinn criter.	4.719010
F-statistic	0.395119	Durbin-Watson stat	1.999320
Prob(F-statistic)	0.529734		

Table 6: Estimation of TGARCH(1,1) and Residual Diagnostics(ARCH LM Test)

Dependent Variable: INDIA_ER
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 10/12/15 Time: 14:10
Sample (adjusted): 1/05/2010 11/24/2014
Included observations: 1275 after adjustments
Convergence achieved after 37 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-1)^2*(RESID(-1)<0) + C(5)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000285	0.000145	1.961117	0.0499
Variance Equation				
C	4.49E-07	1.35E-07	3.317376	0.0009
RESID(-1)^2	0.073199	0.007850	9.325171	0.0000
RESID(-1)^2*(RESID(-1)<...	-0.048224	0.011651	-4.139233	0.0000
GARCH(-1)	0.936501	0.006793	137.8639	0.0000

R-squared	-0.000100	Mean dependent var	0.000343
Adjusted R-squared	-0.000100	S.D. dependent var	0.005809
S.E. of regression	0.005809	Akaike info criterion	-7.642975
Sum squared resid	0.042989	Schwarz criterion	-7.622776
Log likelihood	4877.397	Hannan-Quinn criter.	-7.635389
Durbin-Watson stat	2.055761		

Heteroskedasticity Test: ARCH

F-statistic	0.999169	Prob. F(1,1272)	0.3177
Obs*R-squared	0.999954	Prob. Chi-Square(1)	0.3173

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 10/12/15 Time: 14:19
Sample (adjusted): 1/06/2010 11/24/2014
Included observations: 1274 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.970844	0.076639	12.66780	0.0000
WGT_RESID^2(-1)	0.028017	0.028029	0.999584	0.3177

R-squared	0.000785	Mean dependent var	0.998836
Adjusted R-squared	-0.000001	S.D. dependent var	2.546322
S.E. of regression	2.546323	Akaike info criterion	4.708746
Sum squared resid	8247.344	Schwarz criterion	4.716831
Log likelihood	-2997.471	Hannan-Quinn criter.	4.711783
F-statistic	0.999169	Durbin-Watson stat	1.999389
Prob(F-statistic)	0.317702		

Table 7: Estimation of TGARCH (1, 1) and Residual Diagnostics (ARCH LM Test)

Dependent Variable: INDIA_ER
Method: ML ARCH - Student's t distribution (BFGS / Marquardt steps)
Date: 10/12/15 Time: 14:20
Sample (adjusted): 1/05/2010 11/24/2014
Included observations: 1275 after adjustments
Convergence achieved after 55 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)*RESID(-1)/@SQRT(GARCH(-1)) + C(5)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000265	0.000128	2.073178	0.0382
Variance Equation				
C(2)	-0.432417	0.121192	-3.568031	0.0004
C(3)	0.162723	0.032762	4.966871	0.0000
C(4)	0.066609	0.019802	3.363834	0.0008
C(5)	0.970688	0.010445	92.92889	0.0000
T-DIST. DOF	6.538353	0.975842	6.700216	0.0000

R-squared	-0.000181	Mean dependent var	0.000343
Adjusted R-squared	-0.000181	S.D. dependent var	0.005809
S.E. of regression	0.005809	Akaike info criterion	-7.713058
Sum squared resid	0.042992	Schwarz criterion	-7.688819
Log likelihood	4923.074	Hannan-Quinn criter.	-7.703955
Durbin-Watson stat	2.055594		

Heteroskedasticity Test: ARCH

F-statistic	0.663984	Prob. F(1,1272)	0.4153
Obs*R-squared	0.664681	Prob. Chi-Square(1)	0.4149

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 10/12/15 Time: 14:21
Sample (adjusted): 1/06/2010 11/24/2014
Included observations: 1274 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.997679	0.081486	12.24352	0.0000
WGT_RESID^2(-1)	0.022842	0.028032	0.814852	0.4153

R-squared	0.000522	Mean dependent var	1.021007
Adjusted R-squared	-0.000264	S.D. dependent var	2.722730
S.E. of regression	2.723089	Akaike info criterion	4.842980
Sum squared resid	9432.154	Schwarz criterion	4.851064
Log likelihood	-3082.978	Hannan-Quinn criter.	4.846016
F-statistic	0.663984	Durbin-Watson stat	1.998864
Prob(F-statistic)	0.415309		

Table 8: Residual Diagnostics (Correlogram and Q-Statistics Test for Serial Correlation)

Date: 10/12/15 Time: 14:32
Sample: 1/05/2010 9/16/2015
Included observations: 1275

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob...
		1	-0.04...	-0.04...	2.0455	0.153
		2	-0.02...	-0.02...	2.8880	0.236
		3	0.009	0.007	2.9929	0.393
		4	0.027	0.027	3.9512	0.413
		5	0.026	0.029	4.8425	0.435
		6	-0.00...	0.002	4.8456	0.564
		7	-0.01...	-0.00...	4.9745	0.663
		8	0.020	0.018	5.4905	0.704
		9	0.025	0.024	6.2717	0.712
		1...	-0.01...	-0.00...	6.4371	0.777
		1...	-0.02...	-0.02...	7.1793	0.784
		1...	0.052	0.048	10.606	0.563
		1...	-0.02...	-0.02...	11.230	0.592
		1...	0.007	0.008	11.302	0.662
		1...	0.010	0.011	11.425	0.722
		1...	-0.05...	-0.05...	15.467	0.491
		1...	0.009	0.002	15.574	0.554
		1...	0.037	0.035	17.325	0.501
		1...	0.036	0.042	19.008	0.456
		2...	-0.04...	-0.03...	21.221	0.384
		2...	-0.02...	-0.02...	21.775	0.413
		2...	0.028	0.023	22.766	0.415
		2...	-0.02...	-0.02...	23.379	0.439
		2...	-0.01...	-0.01...	23.641	0.482
		2...	0.042	0.049	25.949	0.410
		2...	0.009	0.010	26.063	0.460
		2...	0.011	0.006	26.208	0.507
		2...	-0.03...	-0.03...	28.148	0.457
		2...	0.022	0.021	28.796	0.476
		3...	-0.00...	-0.00...	28.807	0.528
		3...	-0.02...	-0.02...	29.339	0.552
		3...	-0.00...	-0.00...	29.371	0.600
		3...	0.007	0.007	29.435	0.645
		3...	0.005	0.002	29.473	0.689
		3...	0.023	0.033	30.168	0.700
		3...	-0.04...	-0.04...	32.582	0.632

*Probabilities may not be valid for this equation specification.

Date: 10/12/15 Time: 14:32
Sample: 1/05/2010 9/16/2015
Included observations: 1275

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob...
		1	-0.04...	-0.04...	2.7586	0.097
		2	-0.02...	-0.02...	3.5288	0.171
		3	0.008	0.006	3.6187	0.306
		4	0.036	0.036	5.2552	0.262
		5	0.023	0.027	5.9301	0.313
		6	-0.00...	-0.00...	5.9539	0.428
		7	-0.00...	-0.00...	6.0417	0.535
		8	0.026	0.024	6.9421	0.543
		9	0.026	0.026	7.7796	0.557
		1...	-0.01...	-0.00...	7.9670	0.632
		1...	-0.02...	-0.02...	8.6481	0.654
		1...	0.052	0.047	12.103	0.437
		1...	-0.02...	-0.02...	12.828	0.461
		1...	0.005	0.005	12.863	0.537
		1...	0.008	0.010	12.955	0.606
		1...	-0.05...	-0.05...	16.855	0.395
		1...	0.010	0.003	16.982	0.456
		1...	0.035	0.034	18.577	0.418
		1...	0.034	0.041	20.118	0.388
		2...	-0.04...	-0.03...	22.660	0.306
		2...	-0.02...	-0.02...	23.199	0.333
		2...	0.028	0.023	24.217	0.336
		2...	-0.02...	-0.02...	24.822	0.360
		2...	-0.01...	-0.01...	25.188	0.396
		2...	0.043	0.050	27.596	0.327
		2...	0.007	0.006	27.652	0.376
		2...	0.010	0.006	27.779	0.422
		2...	-0.04...	-0.03...	29.977	0.364
		2...	0.020	0.018	30.515	0.389
		3...	0.002	-0.00...	30.519	0.439
		3...	-0.02...	-0.02...	31.090	0.462
		3...	-0.00...	0.001	31.119	0.511
		3...	0.008	0.007	31.200	0.557
		3...	0.005	0.000	31.229	0.604
		3...	0.021	0.031	31.816	0.623
		3...	-0.04...	-0.04...	34.663	0.532

*Probabilities may not be valid for this equation specification.