International Journal of Science and Research (IJSR)
ISSN (Online): 2319-7064
Impact Factor (2012): 3.358

Table 2: Parameter Estimation of the ARMA (1, 1)-GARCH (1, 1), GJR (1, 1) and DGE (1, 1) Models with the Conditional Distributions

	GARCH			*GJR-GARCH*			*DGE-GARCH*		
Conditional Distribution	*Normal*	*Student t*	*Skewed Student t*	*Normal*	*Student t*	*Skewed Student t*	*Normal*	*Student t*	*Skewed Student t*
Mu(μ)	6.39e -05	2.28e -05	3.55e -06	8.13e -05	5.31e -05	7.06e -05	1.85e -04	6.31e -05	1.59e -04
	(0.4066)	(0.7471)	(0.9646)	(0.3490)	(0.4772)	(0.4754)	(0.00028)	(0.01047)	(0.00506)
ar1 (ϕ_1)	0.8126	0.8314	0.8339	0.8587	0.8717	0.8737	0.8259	0.8832	0.8657
	(< 2e-16)	(< 2e-16)	(< 2e-16)	(< 2e-16)	(< 2e-16)	(< 2e-16)	(< 2e-16)	(< 2e-16)	(< 2e-16)
Ma1 (θ_1)	-0.702	-0.6524	-0.6544	-0.735	-0.6941	-0.6955	-0.6239	-0.6733	-0.6661
	(7.40e-08)	(7.00e-08)	(2.51e-08)	(1.69e-11)	(5.39e-13)	(5.35e-13)	(< 2e-16)	(< 2e-16)	(< 2e-16)
Ljung-Box	7.070	7.452	6.834	7.077	5.692	5.933	15.249	14.809	11.075
TestR^2(Q10)	(0.6610)	(0.6842)	(0.7411)	(0.7181)	(0.8405)	(0.8207)	(0.1232)	(0.1392)	(0.3517)
Ljung-Box	14.436	19.101	19.079	13.758	16.138	16.343	28.621	18.968	14.865
TestR^2(Q15)	(0.4928)	(0.2092)	(0.2102)	(0.5439)	(0.3730)	(0.3596)	(0.0553)	(0.2152)	(0.4612)
Ljung-Box	18.211	22.239	22.086	16.783	19.278	19.649	30.397	21.422	17.356
TestR^2(Q20)	(0.5735)	(0.3277)	(0.3359)	(0.6670)	(0.5038)	(0.4801)	(0.0637)	(0.3727)	(0.6297)
LM Arch Test	10.486	13.978	14.093	8.194	11.988	11.933	19.308	16.457	11.842
	(0.5734)	(0.3021)	(0.2948)	(0.7698)	(0.4467)	(0.4511)	(0.0814)	(0.1712)	(0.4585)
AIC	-7.5364	-7.5775	-7.5626	-7.5502	**-7.5929**	-7.5768	-4.9502	-7.1952	-7.0721
BIC	-7.3962	-7.4040	-7.3758	-7.3867	**-7.4061**	-7.3666	-4.7634	-6.9850	-6.8386

Note: The table shown the t-statistics and p-values are in parentheses for ARMA (1, 1)- GARCH(1,1),GJR(1,1) and DGE(1, 1) models.(AIC) represent Akaike Information Criterion, (BIC) is Bayesian Information Criterion (BIC), Ljung-Box Test R (Standardized Residuals and Ljung-Box TestR^2 (Square Standardized Residual)

The Jarque-Bera statistic to test the null hypothesis of whether the standardized residuals are normally distributed. The results presented in table 3 show that the standardized residuals are leptokurtic and the Jarque-Bera statistic strongly rejects the hypothesis of normal distribution which means that the fat-tailed asymmetric conditional distributions outperform the normal for modeling and forecasting the Sierra Leone exchange rates volatility returns. The Ljung Box tests for the residuals have p-values that are statistically not significant indicating that no serial correlation exists. The Ljung-Box statistics for up to twentieth-order serial correlation of squared residuals are not significant suggesting that no significance correlation exist. As for the LM-ARCH test the results reveals that the conditional heteroskedasticity that existed in the exchange rate returns time series have successfully removed, indicating that no significant appearance of the ARCH effect.

4.1 Forecasting

The forecasting ability of the GARCH models has been discussed precisely by Poon and Granger (2003). We use the R- package 3.0.3 with the "ets" function to evaluate a ten step ahead forecast using 119 observations for the monthly exchange rate returns. The forecasts are evaluated using three different measures which provide robustness in choosing the optimal predicts models for the return series. We consider the following measures.

1). Mean Squared Error (MSE): It quantifies the difference between values with regards the estimator and the true values of the quantity being estimated within a given sample. It is defined as follows

$$MSE = \frac{1}{h+1}\sum_{t=s}^{S+h}\left(\hat{\sigma}_t^2 - \sigma_t^2\right)^2$$

2). Mean absolute error (MAE): It takes into consideration the average of the absolute value of the residuals. It is similar to the MSE but is less sensitive to large errors.

$$MAE = \frac{1}{h+1}\sum_{t=S}^{S+h}\left|\hat{\sigma}_t^2 - \sigma_t^2\right|$$

3). Adjusted mean absolute percentage error: Adjusted Mean Absolute Percentage Error (AMAPE) is a measure based on percentage errors.

$$AMAPE = \frac{1}{h+1}\sum_{t=S}^{S+h}\left|\frac{\hat{\sigma}_t^2 - \sigma_t^2}{\hat{\sigma}_t^2 - \sigma_t^2}\right|$$

Here h is the number of lead steps, S the sample size, $\hat{\sigma}_t^2$ is the forecasted variance and σ_t^2 is the actual variance.

Table 4: Forecasting Analysis for the Exchange rate returns with the Conditional distributions

Exchange rate returns	GARCH			GJR-GARCH			DGE-GARCH		
(Le /USA($)	Normal	Student-t	Skew-t	Normal	Student-t	Skew-t	Normal	Student-t	Skew-t
MSE	0.033	0.032	0.030	0.023	0.021	0.0202	0.029	0.0312	0.0335
MAE	0.574	.524	0.500	0.354	0.327	0.322	0.414	0.400	0.493
AMAPE	0.672	0.662	0.652	0.621	0.612	0.604	0.650	0.649	0.624

Note: MSE denotes the Mean Squared Errors, MAE is Mean Absolute Error, and AMAPE is Adjusted Mean Absolute Percentage Error

The results, as shown in the table 4 above, indicate that the forecasting performance of the GJR-GARCH and DGE-GARCH models, especially when fat-tailed asymmetric conditional distributions are taken into account in the conditional volatility, is better than the GARCH model. However, the comparison between the models with normal, student-t and skewed Student-t distributions shows that, according to the different measures used for evaluating the performance of volatility forecasts, the GJR –GARCH model provides the best forecasts and clearly outperforms DGE-GARCH and GARCH models and the DGE-GARCH model provides less satisfactory forecast results while the poorest forecast results was registered for the GARCH model. Moreover, it is found that the skewed Student-t distribution is more appropriate for modeling and forecasting the exchange rate returns volatility.

5. Conclusion

Modeling exchange rate volatility has received considerable attention from academies, market participant, policy makers, investors and practitioners in recent years as it provide a measure of risk in the financial market. It is important to note that, portfolio selection, asset valuations, risk management, option pricing and hedging strategies provides the importance of modeling and forecasting the conditional volatility of exchange rate returns. This article contributes to the existing literature of volatility modeling and forecasting by the following aspects by estimating and evaluate the forecasting performance of volatility models for exchange rate returns including the ARMA, GARCH, GJR-GARCH, and DGE-GARCH with normal, student-t and skewed Student-t distributions for modelling the Sierra Leones/USA dollar exchange rate returns volatility.

The results show that the forecasting performance of asymmetric GARCH Models (GJR and DGE), especially when fat-tailed asymmetric conditional distributions are taken into consideration in the conditional volatility, is better than GARCH model. The estimated parameters of the Models are statistically significant except, the coefficients of Mu for the GARCH and GJR- GARCH models under the three conditional distributions. Also, the coefficients on the standardized residuals and squared residuals of 10, 15 and 20 and the ARCH effect are not statistically significance which implies that no serial correlation exists in the exchange rate return series and that no significant appearance of the ARCH effect in the returns series and the variance equation is correctly specified.

In relation to the results found with regards the exchange rate markets, the leverage effect term (gamma) in both the GJR-GARCH model and the DGE-GARCH model is statistically significant but negative, indicating that the existence of leverage effect is observed in returns of the exchange rate market . However, according to the different measures used for evaluating the performance of volatility forecasts the GJR-GARCH model under the skewed Student t-distribution provides the best forecasts and clearly outperforms the GARCH and DGE-GARCH models. Moreover, it is found that the skewed Student-t distribution is more appropriate for modeling and forecasting the Sierra Leone/USA dollars exchange rate volatility in particular. Among all of these models, the GJR-GARCH with skewed Student t-distribution gives the highest log-likelihood value and the smallest AIC and BIC values under the student's t-distribution. The overall results, clearly suggests that GJR-GARCH model coupled with a skewed Student t-distribution performs very well with the dataset, and will be more suitable and relevant in facilitating risk management strategy for the Sierra Leone/USA dollars exchange rate returns volatility, which will provide useful information and benchmarks' to investors and policy makers for appropriate decision making in understanding investment strategies and enhancing exchange rate stability in the economy.

Finally, future researches directions could be investigated to improve the modeling Sierra Leone/USA dollars exchange rate volatility which could be better estimated by selecting shorter time intervals as well as introducing long run persistence of shocks in the volatility with fractionally integrated models and asymmetric models (FIGARCH, FIAPARCH, TS-GARCH and EGARCH) that allow to better capture the dynamics of the return series

6. Acknowledgements

We would like to thank the Editor and referees for their comment and valuable suggestions. This work is supported by the National Natural Sciences Foundation of China under the Grants [61175041], [11371077] and the National Natural Science Foundation Research Funds for the Central Universities in China (DUT12LK29).

References

[1] Adjasi, C., H. S. A. D. (2008). 'Effect of exchange rate volatility on the Ghana stock exchange', African Journal of Accounting, Economics, Finance and Banking Research. 3, 28–47.
[2] Aggarwal, R., (1981). "Exchange Rates and Stock Prices: A Study of the US Capital Markets under Floating Exchange Rates"Akron Business and Economic Review, 12, pp. 7-12.
[3] Alberg, D., Shalit, H. and Yosef, R. (2008). Estimating stock market volatility using asymmetric GARCH models. Applied Financial Economics, 18, 1201-1208.
[4] Andersen, T.G., (1994). Stochastic Autoregressive volatility: a framework for volatility modeling. Mathematical Finance 42, 75-102.
[5] Andersen T. and Bollerslev T., (1997). Heterogeneous information arrivals and returns volatility dynamics, Journal of finance, pp. 975–1005.
[6] Andersen, T.G., & Bollerslev,T. (1998). Deutsche mark-dollar volatility: intraday activity patterns, macroeconomic announcements, and longer run dependencies, Journal of Finance, 53, 219-265.
[7] Arifovic J. and Gencay R., (2000). Statistical properties of genetic learning in a model of Exchange rate, Journal of Economic Dynamics and Control, pp. 981–1005.
[8] Baillie, R. T., (1989). The message in daily exchange rates: a conditional variance tale," Journal of Business & Economic Statistics, 7, 297-305.
[9] Baillie, R.T., and Bollerslev, T., (1989).Common stochastic trends in a system of exchange rates. The Journal of Finance 44(1), 167-181.
[10] Balaban, E. (2004). Forecasting exchange rate volatility, working paper.URL: http://ssrn.com/abstract=494482
[11] Barndorff O. E., Nielsen and N. Shephard, (2001). Non-Gaussian Ornstein- Uhlenbeck based models and some of their uses in financial econometrics, Journal of the Royal Statistical Society pp. 167–241.
[12] Beine, M., Laurent S., & Lecourt C., (2000).Central bank intervention and exchange rate volatility: evidence from a regime switching analysis, European Economic Review, 47 (5): 891-911.
[13] Beltratti, A. and Morana C., (1999). Computing value at risk with high frequency data, Journal of Empirical Finance, 6, 431-455.
[14] Bollerslev, T.(1986).Generalized Autoregressive Conditional Heteroskedasticity. J. Econometrics 31,307C27.
[15] Bollerslev, T., Engle, R. F., and Nelson, D. B. (1994). ARCH models. Handbook of econometrics, 4, 2959-3038.
[16] Box, G. E. P., and Jenkins, G.M., (1970). Time series analysis forecasting and control, Holden-Day, San Francisco.
[17] Ding, Z., Granger, Clive W. J. and Engle, Robert F. (1993). A long memory property of stock market returns and a new model. Journal of Empirical Finance, 1, 83-106.
[18] Engle R., (1995). ARCH models, Oxford University Press, Oxford.
[19] Engle, R.F. (1982). Autoregressive conditional heteroscedasticity with estimates of variance of United Kingdom inflation. Econometrica 50, 987-1007.
[20] Fernandez., and Steel, Mark F.,(1998). On Bayesian modeling of fat tails and skewness. Journal of the American Statistical Association, vol.93 (441), 359-371.
[21] Giovannini, A. and Jorion, P., (1987). "Interest Rates and Risk Premia in the Stock Market and in the Foreign Exchange Market"Journal of International Money and Finance, 6, pp. 107-124.
[22] Glosten, Lawrence R., and Jagannathan, Ravi and Runkle, David E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks: The Journal of Finance 48 5, 1779-1801.
[23] Guillaume D., M. Dacorogna, R. Dav´e, U. M¨uller, R. Olsen, and O. Pictet, (1997). From the bird's eye view to the microscope: A survey of new stylized facts of the intraday foreign exchange markets, Finance and Stochastic, pp. 95–131.
[24] Hamilton, J. D. (1994). Time series analysis (Vol. 2). Princeton: Princeton university press.

[25] Hsieh, D.A., (1989) Modeling heteroscedasticity in daily foreign exchange rates, Journal of Business &Economic Statistics, 7, 307-317.
[26] Hung-Chung, L., Yen-Hsien, L. & Ming-Chih, L. (2009). 'Forecasting China Stock Markets Volatility via GARCH Models Under Skewed-GED Distribution.' Journal of Money, Investment and Banking pp. 542–547.
[27] Jensen, M. B. and A. Lunde, (2001). The NIGS and ARCH model: a fat tailed, stochastic, and Autoregressive Conditional Heteroscedastic volatility model," Econometrics Journal, 4, 319-342.
[28] Ken Johnston and Elton Scott, (2000). GARCH models and the stochastic process underlying exchange rate price changes Conditional Volatility and Distribution of Exchange Rates, Journal of Financial and Strategic Decisions Volume 13 Number 2.
[29] Kutty, G. (2010). "The Relationship between Exchange Rates and Stock Prices: The Case of Mexico"North American Journal of Finance and Banking Research, Vol. 4, No. 4, pp. 1-12.
[30] Lambert,P., and Laurent, S.,(2000). Modelling skewness dynamics in series of financial data. Institut de Statistique.
[31] Lambert, P. and Laurent, S. (2001). Modelling financial time series using GARCH-type models with a skewed student distribution for the innovations, Discussion paper 0125,Institut de Statistique, Universit_e Catholique de Louvain, Louvain-la-Neuve, Belgium.
[32] Le Baron B., B. Arthur, and R. Palmer, (1999). Time series properties of an artificial stock market,Journal of Economic Dynamics and Control, pp. 1487– 1516.
[33] Lux T. and Marchesi M., (2000), Volatility clustering in financial markets: a micro simulation of interacting agents, International Journal of Theoretical and Applied Finance, pp. 675–702.
[34] Lux T., (1998).The socio-economic dynamics of speculative markets: interacting agents, chaos, and the fat tail of return distributions, Journal of Economic Behavior and Organization, pp. 143–65.
[35] Marten S.M., (2001). Forecasting daily exchange rate volatility using intraday returns, Journal of International Money and Finance, 20(1), 1-23.
[36] McKenzie M., (1997).ARCH modelling of Australian bilateral Exchange rate data, Applied Financial Economics, 7(2), 147-164.
[37] McKenzie M.,& H.Mitchell, (2002). Generalized asymmetric power arch modelling of exchange rate volatility,Applied Financial Economics, 12(8), 555-564.
[38] Nelson, Daniel B. (1991). Conditional Heteroskedasticity in Asset Returns: A New Approach, Econometrica: Journal of Econometric Society, Vol. 59,347-370.
[39] Olowe, R. (2009). 'Modelling naira/dollar exchange rate volatility: Application of GARCH and Assymetric models.' International Review of Business Research Papers 5, 377–398.
[40] Poon, S.H., and Granger, C. (2003)."Forecasting Volatility in Financial Markets:A Review",Journal of Economic Literature XLI,478-539.
[41] Rahman, Md. L. and Uddin, J. (2009). "Dynamic Relationship between Stock Prices and Exchange Rates: Evidence from Three South Asian Counties"International Business Research, Vol.2, No. 2, pp. 167-174.
[42] Ryan, S. K. & Worthington, A. C. (2004), 'Market, interest rate and foreign exchange rate risk in Australian banking: A GARCH-M approach', International Journal of Applied Business and Economic Research 2, 81–103.
[43] Sanchez-Fung,J.R., (2003). Non linear modelling of daily exchange rate returns volatility and news in small developing economy, Applied Economics Letters 10(4), 247-250.
[44] Taylor, S. (1986). Modeling Financial Time Series. Wiley, New York.
[45] Tse,Y.K., (1998). The conditional heteroscedasticity of the yen dollar exchange rate, Journal of Applied Econometrics,13(1),49-55.
[46] Vilasuso J., (2002). Forecasting Exchange rate volatility, Economics Letters, 76, 59-64.
[47] Wilhelmsson, A. (2006). 'GARCH forecasting performance under different distribution assumptions', Journal of Forecasting 25, 561–578.
[48] Zakoian, Jean-Michel (1994).Threshold heteroskedastic models. Journal of Economic Dynamics and control vol.18 (5), 931-955.