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GJMBR-B Classification : *JEL Code : F31*

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Strictly as per the compliance and regulations of:

Predictive Accuracy of GARCH, GJR and EGARCH Models Select Exchange Rates Application

Ravindran Ramasamy [α] & Shanmugam Munisamy [σ]

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I. Introduction

Forecasting and risk management are the focal points in finance function of business (Arifovic, 2000). The exchange rates assume more importance in the present scenario of globalization. Several univariate and multivariate models are applied in forecasting extensively. The econometric models such as ARMA, GARCH and the extended models like GJR GARCH and EGARCH models are popular. The above models assume Gaussian normal distribution Z ~ iid N(0,1) in forecasting the returns of financial time series (Le Baron, 1999). These models use Gaussian distribution to estimate the future returns using the maximum likelihood (ML) estimations. ML estimation is done through optimization with inequality constraints which not only takes enormous time to solve but also involve iterative processes. This paper aims to compare the efficiency of forecasting of the three models taking ARMA part as constant. The first approach takes the Bollerslev (1992) GARCH as variable element, the second approach takes the GJR GARCH (Glosten, 1993) as the variable element and finally EGARCH of Nelson (1991) as variable element. These models have been extensively debated and proved to be efficient in modeling the returns and volatilities of financial time series (Bollerslev, 1987; Box, 1994). Only a few formal empirical applications have been attempted in judging their accuracy, efficiency, reliability and validation.

The exchange rates (XRs) more important, but less studied variable (Ken Johnston, 2000) when compared to shares, bonds and units. Financial time series tend to be non-stationary (Hamilton, 1994) meaning that additional data will not only change the mean but also the variance, which is an impediment in forecasting. The argument of non stationary nature is taken care of by natural logarithm differencing. The *ln* returns generated are stationary and the returns distribution is approximately Gaussian normal (Brooks, 1998). Few studies prove that the return distributions are not-perfectly normal and they are either skewed or with leptokurtic property with fat tails (Lux, 1998) and show 't' distribution pattern. Any financial time series risk management is concerned about the negative returns at the left tail of a distribution (Beltratti, 1999) and they are to be quantified precisely for effective hedging decisions.

Our paper is application oriented and it compares the predictive accuracy of the three econometric models that forecast the XRs. The remaining part of the paper is organized into five sections. Section two reviews the existing literature in this area on both econometric models and XR forecasting. Section three discusses about the data, volatility, leverage and their efficiency in forecasting financial time series. Section four discusses the results of the analysis and the final section concludes this paper.

II. Literature Review

Volatility is an important parameter in risk assessment and management and it changes as the market prices of financial products change. In international trade the foreign exchange risk

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management is central as these rates change continuously. Modelling their volatility is highly in need to value these reserve assets in banks as demanded by BASEL II and in currency portfolio management (Brooks, 1998). Exporters and importers face transaction and translation losses if not managed properly. A perfect forecasting model is needed to avoid these losses through hedging and to reduce the cost of foreign exchange transaction costs.

In recent years risk assessment models especially in volatility and forecasting focus on three major areas. Firstly, time series forecasting is revolving around the stationarity of data (Pourahmadi, 1988) and to prove non stationarity, unit root testing (Ma, 2000) is applied after differentiation of financial time series data. These ideas were extended to incorporate autoregressive errors and subsequently further extended to ARMA and GARCH models (Engle, 1995). Among them, the prominent area is about volatility modelling attempted by Engle (1982). Later extensions covered not only volatility (Bollerslev, 1986; Andersen, 1997) but also excess kurtosis (Baillie, 1989, 1992; Hsieh, 1989) and volatility clustering (Cont, 2004; Lux, 2000).

The second major area is in determining the distribution for returns generated by financial time series (Barndorff, 2001; Barndorff, 1997). The returns (shocks) created by the price changes in stock market or in currency market are to be modelled for least cost efficient management. Diverse opinions prevail among researchers regarding the shape of the distributions of these returns (Hinich, 1996). Gaussian normal distribution is the most popular among them. But this normal distribution is symmetric and never captures the fat tails (Jensen, 2001), kurtosis and skewness properties (Arifovic, 2000) which are widely prevalent in the returns generated by the financial asset price changes. As an alternative, researchers suggest the student t distribution which roughly captures the above properties. These two distributions are used by researchers to draw random numbers while simulating the future exchange rates. In this paper we use normal distribution for simulation of future XRs.

The third area is regarding the leverage terms. The leverage terms included in the model incorporate the Markovian property of memory of data. The price of a financial asset depends only on the previous day's price and it does not get any contribution from preceding prices (Sarantis, 1999). This assumption is extreme; normally the previous data also contribute but in a lesser weight (Baillie, 1996). This property is accommodated by EGARCH model (Nelson 1991) by including two leverage terms and the volatility is in natural logarithmic form. The Glostan's (1993) GJR model also discusses the importance of another type of leverage. In finance, risk management is all about negative returns as they represent future losses. Positive returns are to be suppressed as they bring profits and not part of risk. To capture the importance of negative returns GJR model introduces two leverage parameters. The model specification is explained in methodology.

The above three areas are researched in isolation (Baillie et al., 1996) like volatility or the nature of distribution etc. This paper incorporates all the above three areas in the model and integrates with ARMA to compute the return and forecasting exchange rates. Though these models have been thoroughly researched in the last two decades still a large gap is uncovered in the practical application (Liew, 2003). For instance, they all model volatility or ARMA individually and they come out with their findings. The volatility and ARMA models ultimately ends up in forecasting the financial time series like share prices and exchange rates (Guillaume et. al, 1997) which are actively pursued not only for buy and sell decisions but also for protecting the asset portfolios. The protection of value of the portfolios is to be carried out for satisfying the investors, regulators, governments and other bodies which invest in these financial instruments substantially. With this background we proceed to elaborate the methodology adopted in analysing and estimating the future XRs.

III. Methodology

Let the daily XRs are denoted by X_t, $t = 0, 1, \ldots, T$ and their *ln* returns at time *t* be

$$R_t = \ln\left(\frac{X_t}{X_{t-1}}\right) \qquad t = 0,\ 1, \ldots, T. \qquad (1)$$

Let $U_t = R_t - \bar{R}$ be the return process where $\bar{R}$ is the mean of *ln* returns of the test sample and U_t be the forecasted return. All GARCH processes try to model the above return process in terms of moving average, conditional variance and autoregressive heteroscedastic variances. The future returns U_t are the total of two components one is based on the U_{t-1} and the other is on the errors ε_t.

$$U_t = \sum_{t=1}^{k} \varphi U_{t-1} + \varepsilon_t \qquad (2)$$

The ε_t is composed of

$$\varepsilon_t = \sigma_t v_t \qquad (3)$$

where

$v_t \sim$ *iid N(0,1)*, a random number drawn from the standard normal distribution.

σ_t = is the volatility of returns

σ^2_t = is the variance of the returns

This σ^2_t is based on the GARCH, GJR and EGARCH.

IV. Garch Model

The generalised autoregressive conditional heteroscedasticity not only takes the lagged error variances but also takes the time lagged variances while modelling volatility. This gives robustness for the model and reduces the forecasting errors. For parsimony, here only two lags are considered though we can include any number of lags.

$$\sigma_t^2 = k + \sum_{i=1}^{P} \Psi_1 \sigma_{t-1}^2 + \sum_{i=1}^{P} \Psi_2 \sigma_{t-2}^2 + \sum_{j=1}^{Q} \varphi_1 \varepsilon_{t-1}^2 + \sum_{j=1}^{Q} \varphi_2 \varepsilon_{t-2}^2 \quad (4)$$

Where

σ_t^2 = Conditional Variance

k = Constant

P = Lag in autoregressive GARCH (P,Q) conditional variance model

Q = Lag in innovations GARCH (P,Q) conditional variance model

Ψ = GARCH coefficient (Variance)

φ = ARCH coefficient (Innovations)

V. The Gjr Volatility Model

The normal distribution is a symmetric distribution which treats both the tails as asymptotic and equal. In financial time series forecasting especially in hedging decisions the left tail is given importance as it represents future losses and these losses are to be hedged. Moreover the return tails are not symmetric (Ding, 1996) and not smooth they are leptokurtic with fat tails. To accommodate these properties and to give more weightage to left tail (Yoon and Lee, 2008) which represents the risk the GJR model induct leverage terms in the conditional volatility model. The volatility model in GJR model is as follows.

$$\sigma_t^2 = k + \sum_{i=1}^{P} \Psi_1 \sigma_{t-1}^2 + \sum_{i=1}^{P} \Psi_2 \sigma_{t-2}^2 + \sum_{j=1}^{Q} \varphi_1 \varepsilon_{t-1}^2 + \sum_{j=1}^{Q} \varphi_2 \varepsilon_{t-2}^2 + \varepsilon_{t-1}^2 * I_{t-1} + \varepsilon_{t-2}^2 * I_{t-2} \quad (5)$$

$$I_{t-1} = \begin{cases} 0, \; if & \varepsilon_{t-1}^2 > 0 \\ 1, \; if & \varepsilon_{t-1}^2 < 0 \end{cases} \quad (6)$$

I_{t-2} also will allow the same leverage effect. If the error is positive it will give a weight of 0 and if it is negative it will assign a weight of 1. This will capture the negative returns more precisely and will help in hedging decisions.

VI. The Egarch Volatility Model

The EGARCH model deals with another problem not addressed by the above two models. In financial time series the recent data is more valuable and contributes more in determining the next day's return as per Markovian principle. The data has no memory (Beran, 1994; Breidt, 1998; Ding, 1983; Granger, 1980; Kirman, 2002; Laboto, 2000) and the recent data only will determine the next return and so on. To give more weightage to the recent data the EGARCH model introduces two changes to the volatility model which is as follows.

$$\log(\sigma_t^2) = k + \sum_{i=1}^{P} \Psi_1 \log(\sigma_{t-1}^2) + \sum_{i=1}^{P} \Psi_2 \log(\sigma_{t-2}^2) + \sum_{j=1}^{Q} \varphi_1 \frac{|\varepsilon_{t-1}^2|}{\sigma_{t-1}^2} + \sum_{j=1}^{Q} \varphi_2 \frac{|\varepsilon_{t-2}^2|}{\sigma_{t-2}^2} + \sum_{j=1}^{Q} \varphi_1 \frac{\varepsilon_{t-1}^2}{\sigma_{t-1}^2} + \sum_{j=1}^{Q} \varphi_2 \frac{\varepsilon_{t-2}^2}{\sigma_{t-2}^2} \quad (7)$$

The first two log volatilities capture the exponential variances the next two standardised autoregressive capture the error effects and the last two standardised components capture the asymmetric negative effects of returns, which is more important in risk assessment.

VII. The Integrated Model

Finally this volatility is combined with the ARMA process to get the next day's return as follows

$$R_t = \mu + \sigma * iid \; N(0,1) \quad (8)$$

The mean μ is arrived in ARMA process and the σ is quantified in one of the GARCH process. The standard normal distribution is used to draw the stochastic process and in combination it produces the next day's return.

$$X_t = R_t + X_{t-1} \quad (9)$$

The current XR is estimated by adding the current return with the previous day's XR. By iteration the entire series of XRs are computed with the MATLAB program.

VIII. Data

To test the efficiency of the forecasting models we have selected four exchange rates which are closely connected with Malaysia in terms of trade and tourism. As such we have chosen exchange rates of Australian Dollar (AUD), Singapore Dollar (SD), Thailand Bhat (TB) and Philippine Peso (PP). While AUD and SD are stronger currencies, TB and PP are soft currencies. We have downloaded the daily exchange rates of the above four currencies from Pacific Exchange rate services website for the period between Jan 2010 and Sept 30, 2011. The data relating to year 2010 is taken for modelling the ARMA, and GARCH coefficients. The computed coefficients were used to predict the exchange rates of 2011 for the whole year. All the three models have been applied to predict the selected four XRs.

Forecasting efficiency of a model is normally tested by the mean square errors they produce. This comparison of errors will not be informative as it is a point estimate. In this paper we not only compute the errors they produce in an iterative manner but also plotted the entire predicted and actual rates to observe the convergence and divergence of the rates. The exchanges rates predicted with different set of Gaussian normal random numbers will give different predicted rates which will make the identification of efficient model difficult. To stop the Gaussian normal random numbers change at every model we put the random state arbitrarily at 100. This state of random numbers will be identical and uniform for GARCH, GJR GARCH and EGARCH models. As all the three models use identical random numbers in all models the predicted exchange rates are comparable. All the three models assume normality in returns of XRs hence they all apply Gaussian normal distribution for simulation of XRs. Uniformly for all the models same initial parameters are applied to assess their efficiency. The model specification is as follows.

Table 1 : Initial values assigned to the model parameters

Distribution:	'Gaussian'			
R:	1			
M:	1			
C:	0.200			
AR:	0.050			
MA:	0.250			
Variance Model:	'GARCH', 'GJR', 'EGARCH'			
P:	2			
Q:	2			
K:	0.300			
GARCH:	Lag 1	0.150	Lag 2	0.200
ARCH:	Lag 1	0.250	Lag 2	0.100
Leverage:	Lag 1	0.050	Lag 2	0.020

For ARMA a lag of 1,1 is applied for autoregressive and moving average components with initial values of 5% and 25% respectively. The constants are arbitrarily assigned an initial vale of 20% for ARMA and 30% for GARCH models. The GARCH, GJR and EGARCH models are assigned with 2 lags to accommodate wider variance and as such four values are given two for volatility and another two for autoregressive component. In addition GJR and EGARCH models are assigned initially two leverage values to capture the importance of negative tail values and to give more weight to recent data which are more important in hedging decisions. Totally six assignments are made and these assignments should not exceed a total value of one and as such the values are distributed as given in the above table. With the above model specifications the GARCH, GJR and EGARCH models are run in MATLAB with a custom made program given in the appendix. The following results are arrived for four XRs.

IX. Australian Dollar

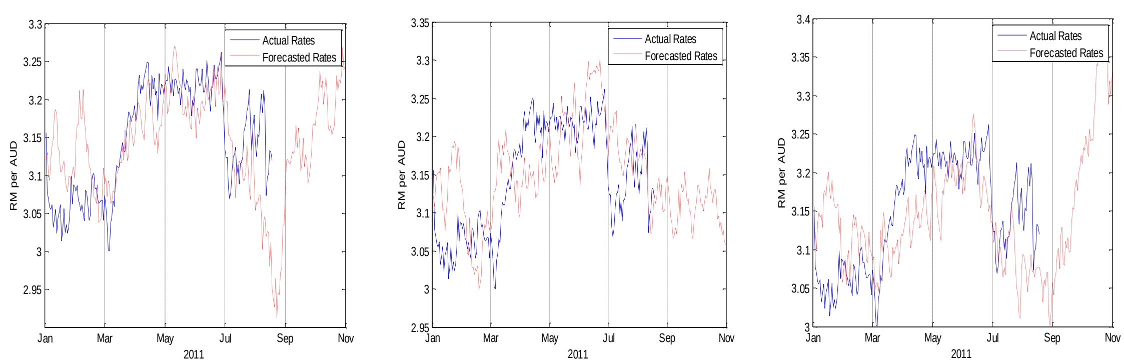
Table 2 : AUD autoregressive coefficients and t values.

	GARCH			GJR			EGARCH		
Parameter	Coeff	Std Err	t value	Coeff	Std Err	t value	Coeff	Std Err	t value
C	0.000	0.001	0.304	0.000	0.001	-0.143	-0.001	0.001	-1.000
AR(1)	-0.264	0.633	-0.417	-0.760	2.664	-0.285	-0.998	0.024	-41.861
MA(1)	0.155	0.641	0.243	0.767	2.631	0.292	1.000	0.040	24.842
K	0.000	0.000	0.677	0.000	0.000	1.126	-2.113	1.501	-1.407
GARCH(1)	0.666	1.468	0.453	0.000	0.560	0.000	0.586	0.593	0.988
GARCH(2)	0.000	1.084	0.000	0.598	0.369	1.621	0.200	0.473	0.423
ARCH(1)	0.035	0.082	0.430	0.000	0.088	0.000	-0.210	0.181	-1.158
ARCH(2)	0.081	0.161	0.507	0.000	0.093	0.000	0.313	0.186	1.682

Leverage(1)		0.248	0.157	1.582	-0.283	0.103	-2.739
Leverage(2)		0.096	0.219	0.441	0.022	0.199	0.109

The XR of AUD against Ringgit Malaysia (RM) is forecasted with ARMA and GARCH coefficients generated with the input data of 2010 under the three famous autoregressive models with one lag for ARMA and two lags for all GRACH models. These coefficients determine the predictive accuracy of forecasted exchange rates (FXRs). The t values determine the strength of the coefficients. Normally they will be converted into probability values and then they will be interpreted. For large samples t value of 1.66 is significant at 10% level and a t value of 1.96 is significant at 5% level.

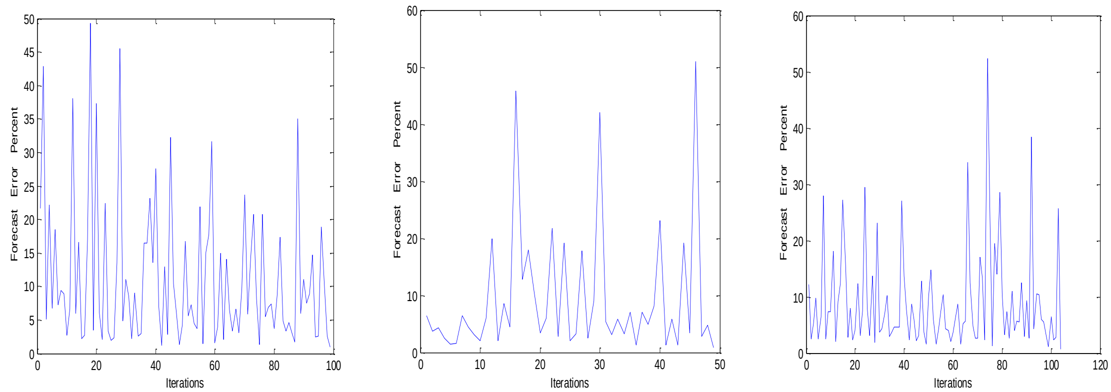
In GARCH model none of the coefficients show t values greater than 1.66 and therefore none of the coefficients is significant in determining the XRs. All the above coefficients contribute for forecasting in a negligible way. In GJR GARCH none of the t values are more than 1.66 therefore under this model also all variables are insignificant and their contribution is negligible. In EGARCH the AR and MA coefficients are significant as their values are high. The AR negatively contributes to the forecasting. In the volatility section the first leverage coefficient also negatively and significantly influences the forecasting. The ARCH(2) coefficient is significant at 10% level of significance. In all models the AR coefficient is negative which implies that the AR pulls down the forecasted XRs but not significantly. The ARCH coefficients in the volatility section are too meagre in value and their contribution is also negligible.



1.a 1.b 1.c

Figure 1 : Convergence of actual and predicted exchange rates.

The convergence of actual and forecasted exchange rates is given in 1.a to 1.c for GARCH, GJR GARCH and EGARCH respectively. In all the three graphs converge nicely form Jan 2011 to Sept 2011. Initially the models forecast badly with upward peaks for a month and then they synchronise well with the actual XR line. In March 2011 the rates sharply fall to RM 3 and in the first 15 days they increase sharply and later it stabilises. The forecasted rates go along with the actual rate line in the later month with minor deviations. In GARCH graph in the month of August 2011 the rates fall very steeply to RM 2.95 but the real rates are stable. The same trend is visible in GJR and EGARCH models. There is no much difference in the above forecasted rates. Since we use an iterative process to get the mini error and a maximum convergence we have to see the iterations the computer takes to reach the minimum error level. To produce an error level less than 5% or less the GARCH model takes 98 iterations while the GJR produces the graph with 49 iterations. The EGARCH model takes 104 iterations to get the results. Both GARCH and EGARCH modes take similar numbers of iterations to reach the same level of convergence. These results imply that the GJR model is suitable for forecasting as it quickly converges to the actual rates.



2.a 2.b 2.c

Figure 2 : Iterations taken to achieve an error level of less than 5 %

Figures 2.a to 2.c show the error levels produced at different number of iterations with the same random number simulations of three GARCH models. The errors do not show any trend or increasing pattern. The XRs predicted are truly stochastic and the iteration numbers show the efficiency of the models. For AUD the GJR model quickly converges.

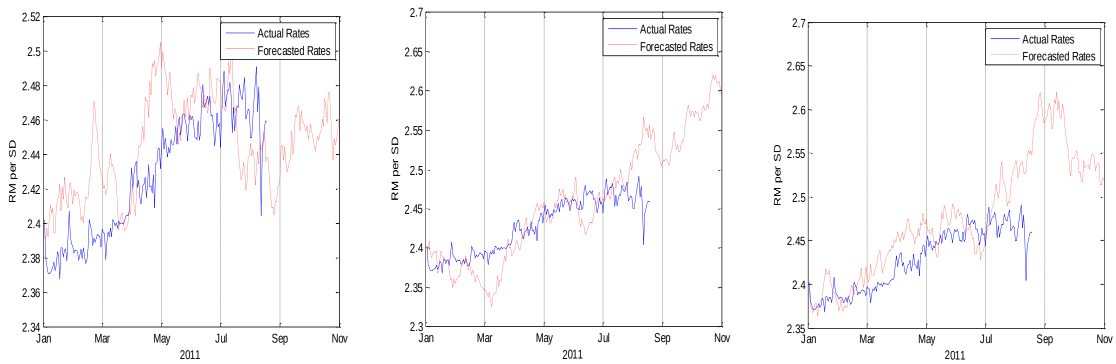
X. Singapore Dollar

The various GARCH coefficients for different models are given in the table below. In the GARCH model only one coefficient GARCH(2) is significant with a t value of 4.247, all other variables are insignificant. As in AUD here also the AR coefficient is negative.

Table 3 : Singapore Dollar autoregressive coefficients and t values.

	GARCH			GJR			EGARCH		
	Coeff	Std Err	t value	Coeff	Std Err	t value	Coeff	Std Err	t value
C	0.000	0.000	-0.052	0.000	0.000	-0.073	0.000	0.000	-0.192
AR(1)	-0.057	0.487	-0.117	-0.935	0.180	-5.199	0.021	0.414	0.050
MA(1)	-0.106	0.475	-0.223	0.916	0.203	4.510	-0.175	0.411	-0.427
K	0.000	0.000	0.939	0.000	0.000	1.257	-0.606	0.344	-1.762
GARCH(1)	0.039	0.158	0.249	0.000	0.064	0.000	1.289	0.282	4.576
GARCH(2)	0.760	0.179	4.247	0.779	0.144	5.415	-0.343	0.279	-1.230
ARCH(1)	0.001	0.031	0.020	0.000	0.000	0.000	-0.276	0.134	-2.061
ARCH(2)	0.083	0.050	1.649	0.148	0.084	1.753	0.373	0.143	2.616
Leverage(1)				0.000	0.000	Inf	0.098	0.078	1.251
Leverage(2)				-0.148	0.088	-1.683	-0.098	0.075	-1.304

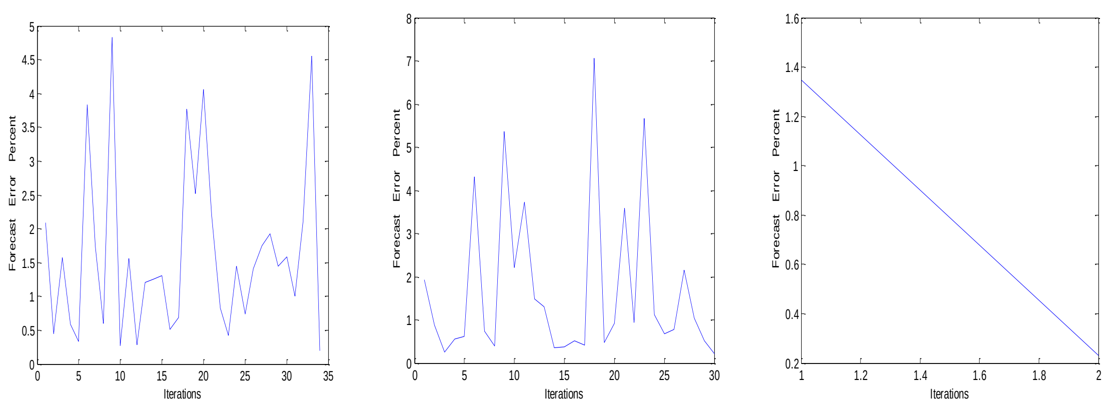
In GJR model AR, MA and GARCH(2) coefficients are significant at 5% level and ARCH and leverage(2) coefficients are significant at 10% level. This model is robust and hence in forecasting the iterations will decrease and the rates will quickly converge. In EGARCH model GARCH(1), ARCH(1) and ARCH(2) are significant at 5% level. The other coefficients are high in values though they are insignificant. Therefore the EGARCH model converges within two iterations. These results show the close economic relationship and the macro economic variables such as interest rate, inflation rate, GDP and balance of payments closely move in tandem in both the countries.



3.a 3.b 3.c

Figure 3 : Convergence of actual and predicted exchange rates

Graphs of Singapore Dollar of the three models are given below. The GARCH graph given in 3.a is more divergent than the GJR figure given in 3.b. and EGARCH in 3.c. Both GJR and EGARCH figures produce the same results in quicker iterations. The GARCH model takes 34 iterations to get the convergence. The convergence is not as efficient as in GJR and EGARCH models. The GJR GARCH takes 30 iterations to reach the same level of convergence. The EGRCH only takes two iterations to produce a good convergence. The results imply that the EGARCH model is suitable to forecast the Singapore Dollar.



4.a 4.b 4.c

Figure 4 : Iterations taken to achieve an error level of less than 5 %

Singapore Dollar rates quickly converge with the actual rates. In EGARCH model it takes only two iterations to forecast the XRs which are close to actual rates. This may be due to the basket of currencies which determine the currency values of both the countries are similar. It may also be due to the close economic relationship existing between both the countries.

X. Thailand Bhat

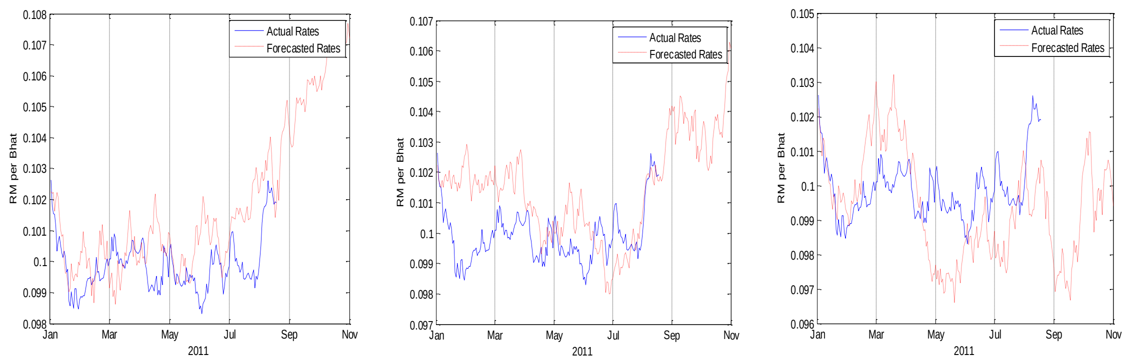
The various model results of TB are given below in the table 4. The first model GARCH whose AR(1), MA(1) and ARCH(2) show significant coefficients at 5% level. GARCH(2) and ARMA constant also show significant coefficients at 10% level. But the convergence takes place only at the 42nd iteration. These results imply that the macroeconomic variables of these two countries differ substantially. The GJR model also exhibit three different coefficients, GARCH (2), ARCH (2) and leverage (2) as significant. This model takes 80 iterations to achieve an error level of less than 5%. These results show the relative efficiency of management of their respective economies.

Table 4 : Thai Bhat autoregressive coefficients and t values

	GARCH			GJR			EGARCH		
	Coeff	Std Err	t value	Coeff	Std Err	t value	Coeff	Std Err	t value
C	0.000	0.000	-0.436	0.000	0.000	0.250	0.000	0.000	0.395
AR(1)	-0.959	0.124	-7.718	-0.577	0.708	-0.815	-0.411	0.756	-0.544

MA(1)	0.967	0.107	9.011	0.516	0.737	0.700	0.335	0.775	0.433
K	0.000	0.000	1.673	0.000	0.000	1.952	-1.334	0.704	-1.895
GARCH(1)	0.208	0.319	0.651	0.160	0.233	0.687	0.253	0.261	0.969
GARCH(2)	0.478	0.282	1.696	0.517	0.186	2.773	0.624	0.238	2.623
ARCH(1)	0.000	0.069	0.000	0.000	0.117	0.000	0.024	0.162	0.148
ARCH(2)	0.189	0.058	3.274	0.324	0.121	2.666	0.367	0.109	3.371
Leverage(1)				0.000	0.125	0.000	-0.054	0.102	-0.534
Leverage(2)				-0.263	0.122	-2.163	0.165	0.085	1.953

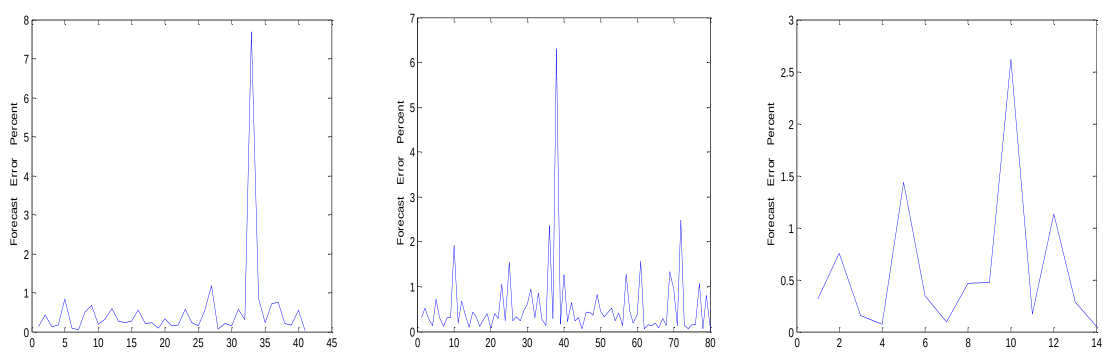
The EGARCH model also shows GARCH (2) and ARCHES(2) significant coefficients. The leverage(2) also significant at 10% level. Though several coefficients are insignificant this model converges quickly within 14 iterations. This result shows the negative association of all coefficients to the predictive accuracy. This may be due to the soft nature of TB against RM.



5.a 5.b 5.c

Figure 5 : convergence of actual and predicted exchange rates

Thailand Bhat's forecasting figures are given in figures 5.a to 5.c. The actual exchange rates (AXR) are closely following the FXR. The GJR model initially overestimates the FXRs for 4 months. The FXRs mostly go above the AXR. Similarly EGARCH model moves but the FXRs go above and below the AXR equally. The GARCH model takes 42 iterations while GJR takes 80 iterations to reach the same level of convergence. But the EGARCH achieves this convergence within 14 iterations. But the EGARCH's convergence is not as good as GARCH and GJR models though it produces similar results.



6.a 6.b 6.c

Figure 6 : iterations taken to achieve an error level of less than 5 %

Figure 6.a and 6.b produce larger errors at the end and at the middle of iterations. Though the coefficients are significant still the GARCH and GJR models do not converge quickly. In EGARCH the coefficients are weak but quickly converge. We attribute this to the relatively weak macro economic variables and economy management as the reasons.

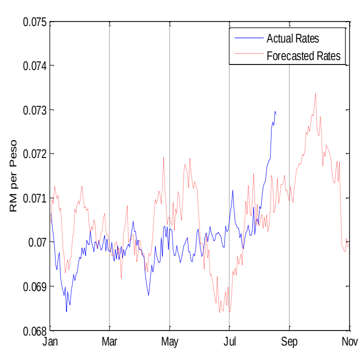
XII. Philippine Peso

Philippine is another closest neighbour of Malaysia but he economic conditions are not similar. The Malaysian Ringgit is stronger than Peso and it depreciates against Ringgit continuously.

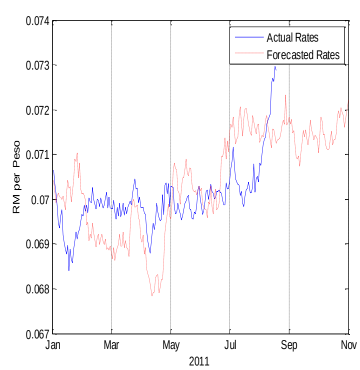
Table 5 : Philippine Peso autoregressive coefficients and t values.

	GARCH			GJR			EGARCH		
	Coeff	Std Err	t value	Coeff	Std Err	t value	Coeff	Std Err	t value
C	-0.001	0.001	-0.958	0.000	0.000	-1.231	0.000	0.000	-0.918
AR(1)	-0.943	1.165	-0.810	-0.105	0.212	-0.497	-0.190	0.253	-0.749
MA(1)	0.942	1.181	0.798	-0.220	0.223	-0.989	-0.067	0.268	-0.249
K	0.000	0.000	0.758	0.000	0.000	0.317	-3.244	3.639	-0.891
GARCH(1)	0.000	1.854	0.000	0.732	3.304	0.222	-0.134	0.171	-0.780
GARCH(2)	0.000	0.676	0.000	0.036	2.594	0.014	0.836	0.166	5.038
ARCH(1)	0.228	0.122	1.869	0.137	0.130	1.057	0.294	0.162	1.811
ARCH(2)	0.093	0.436	0.213	0.000	0.443	0.000	0.074	0.173	0.430
Leverage(1)				-0.088	0.154	-0.568	0.033	0.073	0.447
Leverage(2)				0.036	0.223	0.163	-0.005	0.076	-0.061

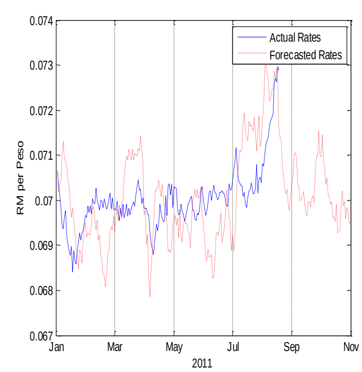
In GARCH model ARCH(1) is only significant that too at 10% level. In GJR model none of the coefficients is significant. In EGARCH the GARCH(2) coefficient alone is significant. The peso is soft when compared to Ringgit and the forecasted rate converges quickly in GJR model than GARCH and EGARCH. The GARCH model takes 18 iterations to produce an error level of less than 5%, while EGARCH takes around 54 iterations. It is observed that in soft currencies when the coefficients are weak the FXR converges quickly towards the AXR.



7.a



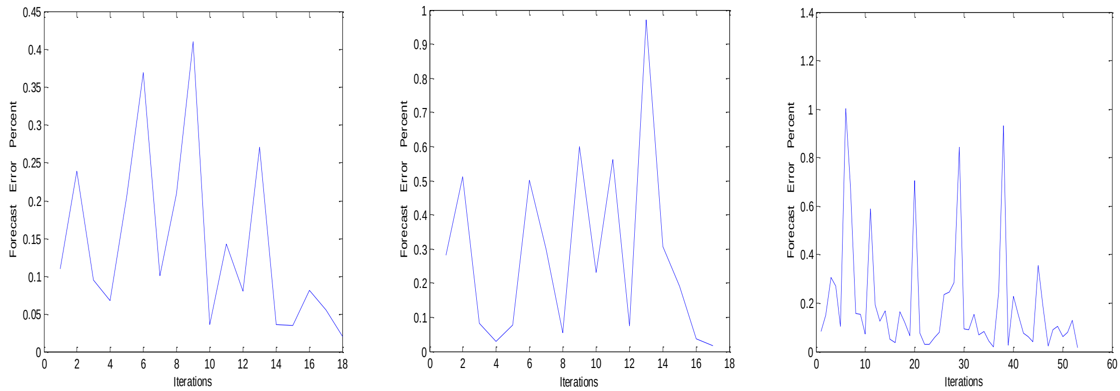
7.b



7.c

Figure 7 : convergence of actual and predicted exchange rates.

The PP figures are given in figures 7.a to 7.c for GARCH, GJR and EGARCH models. The GRACH model achieves FXR in 18 iterations and produces an error level of less than 5%. But the convergence of AXR and FXR does not converge well. Up to June 2011 the forecasted rates go above the actual rates and after that it goes down in July and August 2011and later it increases steeply in Sept 2011. The convergence is not satisfactory though it produces less overall error. The GJR model also shows similar convergence. Though the FXR line follows the AXR line the convergence is not satisfactory. A similar pattern could be observed in EGARCH model also. In this model the sharpness of FXR is more. The AXR is not with valleys and peaks but the FXR is with sharp valleys and peaks. This result is also not satisfactory though it produces less than 5% error.



8.a 8.b 8.c

Figure 8 : iterations taken to achieve an error level of less than 5 %

The pattern of errors produced in different iterations is independent and they never show any trend. Even in the last few iterations the errors are very high and they fall steeply to less than 5% level. Though the coefficients are insignificant the convergence is quicker for PP. EGARCH takes more iterations than the other two models.

XIII. Conclusion

We have forecasted exchange rates by applying three autoregressive models and tested four currencies' exchange rates for their convergence to the actual rates to judge the efficiency of the forecasting ability of the autoregressive models with moving average. The hard currencies' autoregressive coefficients are robust in values but the forecasted rate takes more iteration to converge while soft currencies quickly converge with the actual rates though their coefficients are not so strong. We attribute these phenomena to the macroeconomic variables and management of the economy in these countries. Australia and Singapore tightly manage their economic affairs. They control inflation and show lesser fiscal deficit than Malaysia. Thailand and Philippines economies are not managed as efficiently as Malaysian economy and another reason is there was unrest in Thailand during the study period and in Philippines the economy was affected by floods and cyclones frequently and badly. These economic owes reflected in home currency values and hence actual exchange rates are more volatile than the other two strong currencies. The more volatile exchange rates are modelled by these GARCH models efficiently than the less volatile hard currencies. Among the three models which is more efficient is indeterminable as the models in different currencies produce less error in different number of total iterations. The leverage effect brought in GJR and EGARCH models do not improve the results much. Their effect is negligible. The above models are suitable to predict the future exchange rates though they take different number of iterations, the results are useful for hedging and thus the foreign exchange losses could be avoided.

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Matlab Program

```
Close all
clear all
clc
randn('state',100)

load gerdata

a=data(:,1);p=data(:,2);s=data(:,3);t=data(:,4);
ar1=a(1:250);ar2=a(251:end);

ar=price2ret(a);pr=price2ret(p);
sr=price2ret(s); tr=price2ret(t);

a1=ar(1:250); a2=ar(251:end);
p1=pr(1:250); p2=pr(251:end);
```

```
s1=sr(1:250); s2=sr(251:end);
t1=tr(1:250); t2=tr(251:end);

 %% GARCH Model

spec1=garchset('display','off');
spec2=garchset(spec1,'R',1,'M',1,'C',.2,'AR',.05,'MA',.25,'K',.3,...
'P',2,'Q',2,'GARCH',[0.25,0.20],'ARCH',[0.15,
0.1],'Variancemodel','GARCH');

e=3;
n=0;
while (e>1)
        e=0;
        [coeff errors]=garchfit(spec2,a1);
        spec3=garchset(coeff);
        asim=garchsim(spec3,249,1);
        asr=ret2price(asim,a(250));
        asrate=asr;
        acr=asrate(1:189);
        e2=sum((acr-ar2).^2);
        eadg(n+1)=e2     % Error Australian Dollar GARCH
        e=e2;
        n=n+1
end

 figure
 plot([1:189],ar2,[1:250], asr,'r:','LineWidth',0.5)

set(gca,'XTickLabel',{'Jan','Mar','May','Jul','Sep','Nov'},'XGrid','on')
 xlabel('2011','FontSize',10)
 ylabel('RM per AUD','FontSize',10)
 legend('Actual Rates','Forecasted Rates')

  %% GJR Model With Leverage

spec1=garchset('display','off');
spec2=garchset(spec1,'R',1,'M',1,'C',.2,'AR',.05,'MA',.25,'K',.3,...
'P',2,'Q',2,'GARCH',[0.25,0.20],'ARCH',[0.15,
0.1],'L',[0.05,0.02],...
'Variancemodel','GJR');

e=3;
n=0;
while (e>1)
        e=0;
        [coeff errors]=garchfit(spec2,a1);
        spec3=garchset(coeff);
        asim=garchsim(spec3,249,1);
        asr=ret2price(asim,a(250));
        asrate=asr;
        acr=asrate(1:189);
        e2=sum((acr-ar2).^2);
eadjr(n+1)=e2   % Error Australian Dollar GJR
e=e2
        n=n+1
end

figure
plot([1:189],ar2,[1:250], asr,'r:','LineWidth',0.5)

set(gca,'XTickLabel',{'Jan','Mar','May','Jul','Sep','Nov'},'XGrid','on')
 xlabel('2011','FontSize',10)
 ylabel('RM per AUD','FontSize',10)
 legend('Actual Rates','Forecasted Rates')

 %% EGARCH Model With Leverage

spec1=garchset('display','off');
spec2=garchset(spec1,'R',1,'M',1,'C',.2,'AR',.05,'MA',.25,'K',.3,...
'P',2,'Q',2,'GARCH',[0.25,0.20],'ARCH',[0.15,
0.1],'L',[0.05,0.02],...
'Variancemodel','EGARCH');

e=3;
n=0;
while (e>1)
        e=0;
        [coeff errors]=garchfit(spec2,a1);
        spec3=garchset(coeff);
        asim=garchsim(spec3,249,1);
        asr=ret2price(asim,a(250));
        asrate=asr;
        acr=asrate(1:189);
        e2=sum((acr-ar2).^2);
        eadeg(n+1)=e2     % Error Australian Dollar EGARCH
        e=e2
        n=n+1
end

figure
plot([1:189],ar2,[1:250], asr,'r:','LineWidth',0.5)

set(gca,'XTickLabel',{'Jan','Mar','May','Jul','Sep','Nov'},'XGrid','on')
xlabel('2011','FontSize',10)
ylabel('RM per AUD','FontSize',10)
legend('Actual Rates','Forecasted Rates')
```