Exchange Rate Forecasting – An Application of Higher Order ARIMA and GARCH Models

Ravindran, Ganisen and Roslan

Foreign exchange risk management is a new challenging area the finance managers face at present. Accurate forecasted exchange rates are essential for hedging decisions especially after globalization. It is all the more important now as the USD is depreciating and world is facing abnormal oil price and food price increases. An attempt was made to estimate the parameters of ARIMA and GARCH and apply them to simulate and predict the exchange rates. Testing the forecasting accuracy of higher order lags of ARIMA and GARCH models using US Dollar – Malaysian Ringgit (US_{XR}) exchange rate is the theme of the paper. The ARIMA and GARCH parameters were estimated by MATLAB software using daily exchange rates' returns of 2006-07. Ex-ante returns were simulated and predicted simultaneously by using the estimated parameters and plotted together with real US_{XR} of 2007-08 to visually verify the fit. The divergence error was also computed to find the accuracy of forecasting. Our results indicate the simulated and the predicted exchange rates are almost overlapping on the real US_{XR} of 2007-08 in four models. Two models in prediction [2 1 1 2], [2 1 2 2] and two models in simulation [1 1 1 1], [2 1 1 1] give efficient forecasting results. The trend in US_{XR} is captured by all models but with some error. This lends support to the claim that some financial time series are not entirely random and the chartists' techniques are valid. Time series historical data can be used to achieve more or less accurate forecast which could be used in hedging strategies.

Field of Research: Finance, Foreign Exchange Risk Management

1. Introduction

Extensive research has been carried out on the returns of time series data using Autoregressive Integrated Moving Average (ARIMA) Generalized Autoregressive Conditional Heteroscedastic (GARCH) models during the last two decades. The earlier studies of time series forecasting in share prices, yield rates and exchange rate (Zhang, 2001) movements fall broadly into two categories namely

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those that rely on technical analysis using historical data and graphs (Harvey 1990, Diebold 1989) and those that rely on fundamental analysis (Edward 1998, Kenneth 1994) employing macro economic variables. The technical analysis approach uses only historical time series data like ex-post exchange rates (XRs) to determine the trend and to model volatility.

The use of technical analysis goes against the efficient market hypothesis and academic opinion due to random walks (Brownian Motion) present in the time series (Nelson Plosser, 1982). The efficient market hypothesis asserts that the time series variables reflect all the available information that can be obtained through various sources like wire information, websites and newspapers already reflected in prices and no one can predict the future movements. The increase and decrease noticed are purely a random white noise which are independent and identically distributed. The random walk theory also suggests that past information cannot be used as a guideline to predict the future movement of the time series variables (Darrat, 2000). The behaviour of time series variables such as XRs is not consistent and to forecast it is irrational. Despite these assertions many multinational corporations, dealers in foreign exchange, exporters, importers and speculators continue to make hedging decisions based on forecasted rates using ex-post data as the basis. These hedging decisions are made under the premise that patterns exist in the ex-post data and these patterns provide an indication of future movement of XRs at least in the short run. If such patterns exist then it is possible in principle to apply modern mathematical tools and techniques such as ARIMA and GARCH to forecast the ex-ante XRs (Hamilton 1994, Klaassen 1998).

2. Literature Review

The autoregressive integrated moving average (ARIMA) introduced by Box Jenkins (1976) analyzes and forecasts equally spaced univariate time series data. An ARIMA model predicts mean values in a time series as a linear combination of its own past values and past errors (Nelson, 1991). The idea behind this is the time series variable has own correlation not with another time series variable, but its own, when they are compared within by giving a lag (time difference). The ARIMA procedure provides methodology and procedure for univariate time series parameter estimation and forecasting of mean returns. Similarly the GARCH model advocates that there is correlation between a time series data and its own lagged data. These models have been widely used in predicting several time series data including inflation (Engle 1982, Bollerslev 1986), stock prices (Schwert 1989, Hamilton and Susmel, 1994, Cho and Engle 1999), exchange rates (West and Cho 1994), interest rates (Bernlt 1974, 31996, Edwards 1998) and for forecasting (Hamilton and Susmel 1994, Campa and Chang 1997, and Klaassen 1998).

Most of the earlier research studies were carried out with extensive algebra and a few empirical tests (Cheung, 2005) were carried out in applying ARIMA and

GARCH especially in higher lags due to enormity of the calculations involved. The goodness of fit to the actual data was also explained through the sums of squares. The earlier studies modeled the moving average, variance and errors separately and not attempted to synchronize all of them. They stop with modeling the parameters but not attempted to integrate the differenced data to original time series and compare the goodness of fit. In this paper we have addressed the above deficiencies and have shown graphically the goodness of fit. In addition we have computed the sums of squares between the real and forecasted data to compare the accuracy of our forecasts. This paper is organized into five sections of which section two reviews the literature, section three explains the methodology applied in forecasting the parameters of ARIMA and GARCH models in various time lags and sources of data. Section four presents the results of analysis and the errors of prediction and simulation in relation to real rates. Section five concludes this paper.

3. Methodology

Extensive algebraic analyses were carried out in time series variables such as share prices to establish the normality, stationarity, pattern of shocks, conditional mean, variance (Kin Yip, 2007), innovations, etc (Engle, 1982, Nelson, 1991). Another branch of research dealt with the autocorrelations and partial autocorrelations to establish fat tails present in time series data. Yet another group of studies revolve around unit root testing (Al-Zoubi, 2008), co-integration testing and time varying nature of the time series data. Very few studies have applied prediction and simulation techniques to forecast (Amano, 1986) and compare the accuracy of the forecasting of the ARIMA and GARCH models. Even in forecasting researchers tried with lower level lags and stop with either ARIMA or GARCH model (Klaassen, 1998) and not with both. This study incorporates higher lags and attempts prediction and simulation simultaneously in forecasting.

Pure time series variables exhibit trend and non-stationary characters which are unsuitable for forecasting and modeling. Past researchers use return series especially log returns assuming that the returns are log normally distributed. The famous Black Scholes model for pricing European options uses log normal returns. We also assume that the returns are independent and identically distributed in log normal form. Normally the returns are computed either on percentage basis (p_1/p_0-1) or on log price basis ($\log p_1 - \log p_0$) or ($\log (p_1/p_0)$). In this study as in Black Scholes model log returns are computed and used to estimate the ARIMA and GARCH parameters.

$$R_t = \log\left(\frac{p_t}{p_{t-1}}\right) \tag{1}$$

R_t = Return

P_t = Current rate
P_{t-1} = Previous day rate

This is accomplished by MATLAB `price2ret` function.

The differenced daily returns are used for estimating the parameters of ARIMA and GARCH models. Equations 2 and 4 use one-day lag to estimate the coefficients and equations 3 and 5 use two days lag to estimate the same parameters. The estimated coefficients are used to predict and simulate the future returns assuming that the same pattern will prevail in the time series future returns. The ARIMA computes the moving average parameters while the GARCH quantifies the variance parameters through the following syntaxes.

$$ym_t = c + \sum_{i=1}^{R} \phi_1 y_{t-1} + \sum_{j=1}^{M} \theta_1 \varepsilon_{t-1} \quad \text{(i, j =1,2………)} \qquad (2)$$

$$ym_t = c + \sum_{i=1}^{R} \phi_1 y_{t-1} + \sum_{i=1}^{R} \phi_2 y_{t-2} + \sum_{j=1}^{M} \theta_1 \varepsilon_{t-1} + \sum_{j=1}^{M} \theta_2 \varepsilon_{t-2} \quad \text{(i, j =1,2………)} \qquad (3)$$

ym_t = Average return
C = Constant
R = Lag (in days) for moving average
M = Lag (in days) for error
ϕ = Moving average coefficient
θ = Error coefficient
ε = Noise or innovations or errors

The returns are decided by two components. They are the time series data itself with one day lag and the other is the error with one day lag. In case of two days lag an additional term is added to each existing parameter with two days lag. The interpretation of the parameters is just like regression coefficients computed based on the principle of least squares.

The Variance in returns is computed with the following syntaxes.

$$\sigma_t^2 = k + \sum_{i=1}^{P} \psi_1 \sigma_{t-1}^2 + \sum_{j=1}^{Q} \varphi \varepsilon_{t-1}^2 \quad \text{(i, j =1,2………)} \qquad (4)$$

$$\sigma_t^2 = k + \sum_{i=1}^{P} \psi_1 \sigma_{t-1}^2 + \sum_{i=1}^{P} \psi_2 \sigma_{t-2}^2 + \sum_{j=1}^{Q} \varphi_1 \varepsilon_{t-1}^2 + \sum_{j=1}^{Q} \varphi_2 \varepsilon_{t-2}^2 \quad \text{(i, j =1,2………)} \qquad (5)$$

σ_t^2 = Current Variance
k = Constant
P = Lag (in days) for variance
Q = Lag (in days) for errors
Ψ = Variance coefficient
φ = Error coefficient

The variance is also decided by two components as in returns. One is the previous day's variance and the other is the previous day's error. If the model uses two days lag an additional term is added in variance and in error.

The above parameters estimated with the ARIMA (C, ϕ and θ) and GARCH (K, Ψ and φ) models are used to simulate and predict the time series returns. These returns are converted back to ordinary time series by integration.

$$p_t = R_i \times p_{t-1} \tag{6}$$

P_t = Current rate
R_i = Return
P_{t-1} = Rate of previous day

This is carried out through MATLAB `ret2price` function.

The prediction technique computes returns by minimizing the mean squared error (Ince, 2006; Jyh-Lin, 2001) as in the maximum likelihood estimation (Sowell, 1992) while simulation computes returns based on normally distributed random numbers as in the Monte Carlo Simulation. The real exchange rates of 2007-08 and the rates computed through prediction and simulation are plotted in a single graph to observe the fit and validation. To find the deviation of the forecasted lines from the real line numerically the difference between simulated rate and real rate, predicted rate and real rate are computed, squared and summed up as follows.

$$\varepsilon = \sum_{i=1}^{n} \left(Fr_i - Rr_i \right)^2 \qquad (i = 1,2\ldots\ldots n) \tag{7}$$

ε = Total error
Fr_i = Forecasted rate either by simulation or by prediction
Rr_i = Real exchange rate of 2007-08

To test the forecasting ability of the ARIMA and GARCH models, exchange rate data of US Dollar- Malaysian Ringgit (US_{XR}) was downloaded form the Pacific Exchange rate service website (http://fx.sauder.ubc.ca/data.html), from 1st April 2006 to 31st March, 2008. The US_{XRs} were divided in to two parts, rates pertaining to 2006-07 are treated as basic sample for calculating ARIMA and GARCH parameters and the US_{XR} relating to 2007-08 were treated as validation sample. The daily exchange rates of 2006-07 were converted into log returns and applied in estimation of the ARIMA and GARCH parameters at various higher order time lags. The estimated coefficients are used to predict and simulate US_{XR} returns using the following ten ARIMA and GARCH models. The returns are reconverted in to actual exchange rates (integration) for plotting.
The following models were tested.

1. ARIMA and GARCH lags [0,0, 1,1] and [1,1, 1,1]
2. ARIMA and GARCH lags [1,1, 1,2] and [1,1, 2,1]
3. ARIMA and GARCH lags [1,1, 2,2] and [2,1, 1,1]
4. ARIMA and GARCH lags [2,1, 1,2] and [2,1, 2,1]
5. ARIMA and GARCH lags [2,1, 2,2] and [2,2, 2,2]

The first two numbers in the square brackets denote ARIMA lags, first number being Autoregressive lag, the second number is lag for Moving Average for returns. The third number is for Variance (GARCH) and the fourth number is for error (ARCH) to capture variances. The above ARIMA and GARCH models are used first to model the parameters required for simulation and prediction. This is done by the MATLAB software by taking errors as the objective function to minimize. The parameters are estimated considering maximum likelihood estimation by minimizing the mean squared errors. The parameters computed are used for estimation of future returns through Monte Carlo simulation method. Secondly we predict the returns by minimizing the mean squared errors.

4. Results and Discussion

The data was analysed with the help of MATLAB software by using GARCH toolbox functions. First the MATLAB default model was tried and then the higher models were analysed. The outputs are given in pairs. In all tables the first column gives the names of parameters, the second column shows the parameter values and the third column exhibits the standard errors. The ‘t’ values are given in the final column which is arrived at by dividing the value of the parameter by the standard error. When the ‘t’ value exceeds 2.00 it would be considered as significant which means this particular parameter is highly influential in forecasting the return of this series.

ARIMA and GARCH lags [0,0, 1,1] and [1,1, 1,1]

In this model the constants of ARIMA and GARCH, C and K are only used for prediction of US_{XR}. This is the default model in MATLAB software. The results are given in the first section of the table one. The first four columns show the results of the default model where only constants are given and their value is very small. Hence the table shows zero values. Of course there will be values in the fourth or in fifth decimal place and hence there are ‘t’ values. The second part four columns show the results of the other model which is ARIMA (1,1) and GARCH (1,1). All parameters are significant as their ‘t’ values are more than two. The AR coefficient shows negative sign, whose contribution is negative in determining the return of the US_{XR}. The contribution of all parameters in prediction and simulation of returns is robust.

Table 1 ARIMA and GARCH parameter for [0,0, 1,1] and [1,1, 1,1] lags

Mean: ARIMAX(0,0,0); Variance: GARCH(1,1)				Mean: ARIMAX(1,1,0); Variance: GARCH(1,1)			
Parameter	Value	Std Error	‘t’ Value	Parameter	Value	Std Error	‘t’ Value

C	0.000	0.000	-1.640	C	0.000	0.000	-1.370
K	0.000	0.000	16.807	AR(1)	-0.264	0.039	-6.785
				MA(1)	0.281	0.039	7.201
				K	0.000	0.000	2.224
				GARCH(1)	0.769	0.050	15.513
				ARCH(1)	0.217	0.056	3.899

The above parameters in the second part four columns are to be interpreted as in linear regression which estimates the coefficients by method of least squares.

$$y_t = 0.000 - 0.264 X_{t-1} + 0.281 \varepsilon_{t-1} \quad (8)$$

$$\sigma^2 = 0.000 + 0.769 \sigma_{t-1} + 0.217 \varepsilon_{t-1} \quad (9)$$

The simulated and predicted returns are converted into specific exchange rates and plotted to see visually how they move or follow the real US_{XR} in 2007-08. The trends present in the three US_{XR} rates are illustrated in the figures 1.a and 1.b. The thin black line shows the movement of real US_{XR}. The thick dark line is the simulated US_{XR} and the dotted line is the predicted US_{XR} for 2007-08.

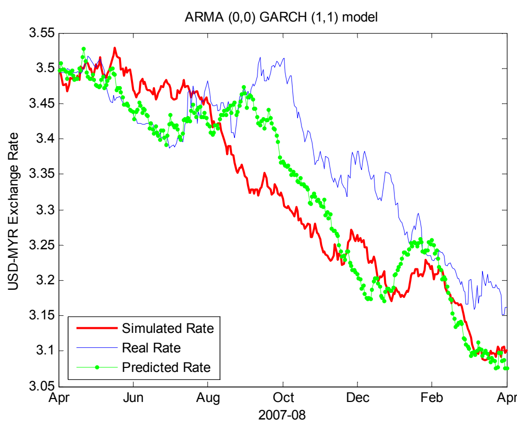


Figure 1.a

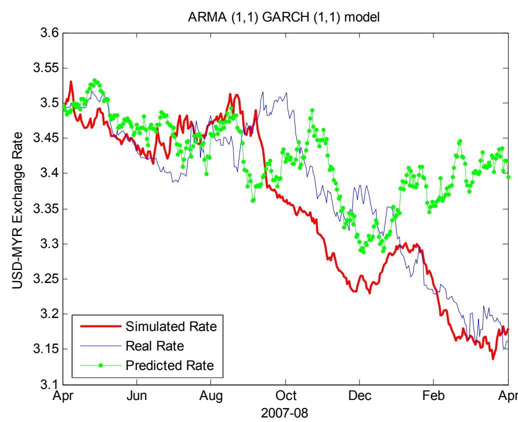


Figure 1.b

Simulation Error 2.595; Prediction Error 1.673 Simulation Error 1.127; Prediction Error 3.093

In the above figure 1.a both the simulated and predicted US_{XR} follow the real US_{XR} in trend. The predicted US_{XR} line is close to the US_{XR} while the simulated rate line is moving far below the real US_{XR}. Both simulated and predicted US_{XR} underestimate the returns over the period of 12 months. In February 2008 all the three US_{XR} are converging very close to each other. In figure 1.b the three lines move together up to August and later the predicted line goes up causing a larger error. The simulated line follows the trend of the real line but goes below till January 2008 and later it goes closer to the real line. The deviation errors are given below the figures. In figure 1.a the predicted error is less while in figure1.b the simulated line shows lesser error. Smaller error shows a better fit.

ARIMA and GARCH lags [1,1, 1,2] and [1,1, 2,1]

The parameter values of model [1,1, 1,2] are given in the first four columns and the model [1,1, 2,1] values are given in the final four columns of the Table 2 below.

Table 2 ARIMA and GARCH parameter for [1,1,1,2] and [1,1,2,1] lags.

Mean: ARIMAX(1,1,0); Variance: GARCH(1,2)				Mean: ARIMAX(1,1,0); Variance: GARCH(2,1)			
Parameter	Value	Std Error	‘t’ Value	Parameter	Value	Std Error	‘t’ Value
C	0.000	0.000	-1.662	C	0.000	0.000	-1.257
AR(1)	0.524	0.025	20.807	AR(1)	-0.048	0.041	-1.170
MA(1)	-0.519	0.025	-20.669	MA(1)	0.069	0.039	1.783
K	0.000	0.000	2.468	K	0.000	0.000	1.694
GARCH(1)	0.755	0.049	15.318	GARCH(1)	0.772	0.414	1.865
ARCH(1)	0.076	0.059	1.292	GARCH(2)	0.000	0.333	0.000
ARCH(2)	0.154	0.070	2.198	ARCH(1)	0.214	0.091	2.341

AR and MA one day lag parameters show robust ‘t’ values indicating their importance in prediction and simulation. GARCH (1) is also robust whereas the contribution of ARCH (1) and (2) are negligible. In the [1,1, 2,1] model all the parameters lose their significance when GARCH lag is increased from one to two and none of them is significant. All ‘t’ values are less than two. When GARCH lag increases the model parameters becomes weak in prediction and simulation.

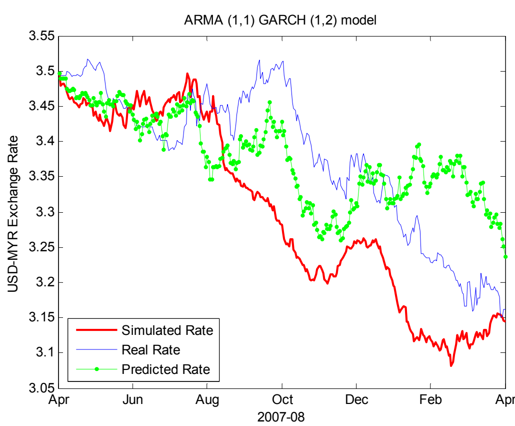


Figure 2.a

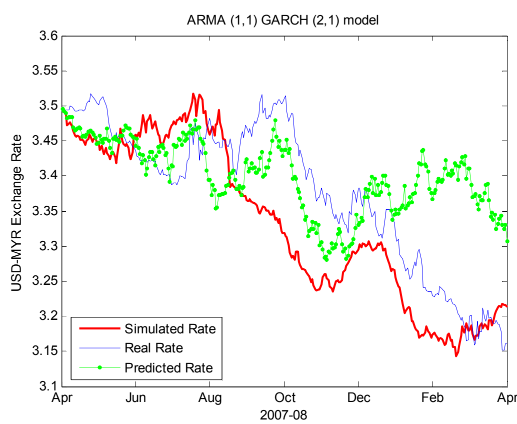


Figure 2.b

Simulation Error 3.573; Prediction Error 1.917 Simulation Error 2.027; Prediction Error 2.611

Form April 2007 to October 2007 figure 2.a shows that the three lines synchronize closely. The simulated thick line falls sharply afterwards when compared to the real US_{XR} line, while the predicted US_{XR} line follows a middle path up to January 2008. Afterwards all lines converge and come closer to each other. In April 2008 almost the real and simulated lines meet each other. A closer observation reveals that the trend is accurately captured by the simulated line as in real line. Figure 2.b also behaves similar to figure 2.a. The real line and simulated lines go hand in hand, but the predicted line increases sharply and goes away from the real line in January 2008. Due to this the error of predicted line is greater though the line is closer to real line in the beginning. The prediction error is less when compared to the simulation error in figure 2.a.

ARIMA and GARCH lags [1,1, 2,2] and [2,1, 1,1]

The first four columns of table 3 show the parameter values of [1,1, 1,2] lags of ARIMA and GARCH. Columns five to eight show the parameter values of lags of [1,1, 2,1]. In the first part, except ARCH (1) all other parameters are insignificant. It shows that these parameters' influence is negligible in forecasting the US_{XR}. In the second part all parameters are significant except AR (2) which shows a negative coefficient with a lower 't' value, whose contribution in prediction of US_{XR} is meager.

Table 3 ARIMA and GARCH parameters for [1,1,2,2] and [2,1,1,1] lags.

Mean: ARIMAX(1,1,0); Variance: GARCH(2,2)				Mean: ARIMAX(2,1,0); Variance: GARCH(1,1)			
Parameter	Value	Std Error	't' Value	Parameter	Value	Std Error	't' Value
C	0.000	0.000	-1.419	C	0.000	0.000	-0.706
AR(1)	-0.049	0.038	-1.289	AR(1)	0.822	0.269	3.053
MA(1)	0.092	0.049	1.888	AR(2)	-0.051	0.080	-0.643
K	0.000	0.000	2.114	MA(1)	-0.810	0.270	-2.994
GARCH(1)	0.515	0.469	1.097	K	0.000	0.000	2.150
GARCH(2)	0.196	0.405	0.484	GARCH(1)	0.767	0.053	14.495
ARCH(1)	0.064	0.057	1.130	ARCH(1)	0.227	0.059	3.824
ARCH(2)	0.204	0.087	2.348				

The US_{XR} for 2007-08 were simulated and predicted using the parameters estimated from 2006-07 US_{XR} data. In figure 3.a the trend of real line and the simulated US_{XR} line is similar though there are gaps at certain months. Up to August 2007 both the line stay up in sync but from August 2007 onwards the real line stays up while the simulated US_{XR} line declines and goes along with the real US_{XR} line but with a gap.

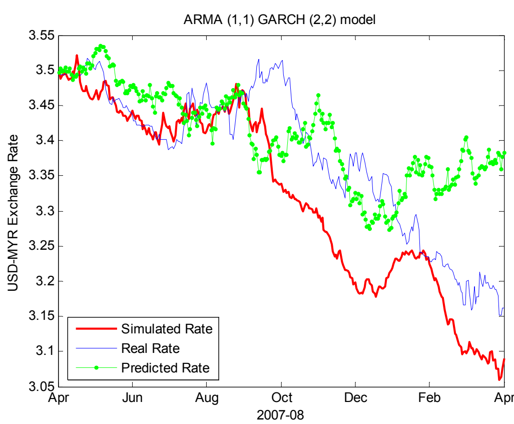


Figure 3.a

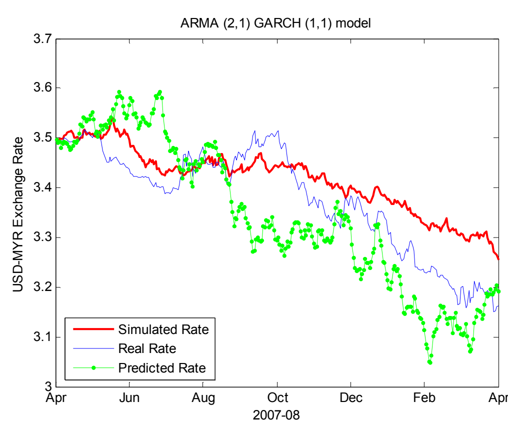


Figure 3.b

Simulation Error 2.013; Prediction Error 2.277 Simulation Error 1.197; Prediction Error 3.002

In February 2008 both the lines meet and again the simulated US_{XR} line goes down. The predicted line is in sync with the real US_{XR} line up August 2007 and later it shows some mix up till February 2008. Later it shows an increasing trend while the actual US_{XR} line goes down, showing greater divergence. Figure 3.b shows an unclear trend. The simulated line is flatter than the predicted line and real line. The predicted line closely follows the trend of the real line but with wider divergence in June and in October 2007. The errors below the figures show how close the lines are to the real line. Lower error shows the proximity of the lines. In both the figures the simulated line shows lesser error.

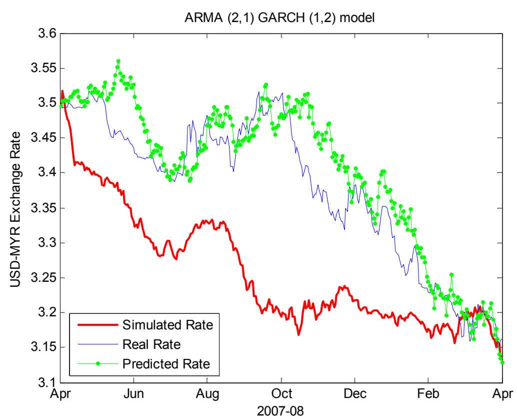
ARIMA and GARCH lags [2,1, 1,2] and [2,1, 2,1]

Table four gives the parameter values of ARIMA and GARCH for [2,1,1,2] and [2,1,2,1] lags.

Table 4: ARIMA and GARCH parameters for [2,1,1,2] and [2,1,2,1] lags.

Mean: ARIMAX(2,1,0); Variance: GARCH(1,2)				Mean: ARIMAX(2,1,0); Variance: GARCH(2,1)			
Parameter	Value	Std Error	't' Value	Parameter	Value	Std Error	't' Value
C	0.000	0.000	-0.665	C	0.000	0.000	-0.623
AR(1)	0.828	0.310	2.669	AR(1)	0.819	0.297	2.756
AR(2)	-0.077	0.076	-1.016	AR(2)	-0.051	0.085	-0.593
MA(1)	-0.786	0.320	-2.458	MA(1)	-0.806	0.306	-2.637
K	0.000	0.000	2.367	K	0.000	0.000	1.728
GARCH(1)	0.749	0.054	13.817	GARCH(1)	0.766	0.431	1.777
ARCH(1)	0.080	0.071	1.131	GARCH(2)	0.000	0.344	0.000
ARCH(2)	0.159	0.081	1.953	ARCH(1)	0.228	0.104	2.205

The first part of table four, three variables are significant in terms of 't' values. AR (1) and MA (1) show lower 't' values of 2.67 and negative 2.46 approximately, while GARCH (1) shows a 't' value of 13.8. These parameters significantly influence the exchange rates in 2006-07. The other parameters are insignificant. In the second part of the table three coefficients AR (1), MA (1) and ARCH (2) show significant 't' values, but their level of significance is low. The other variables are insignificant and they play a negligible role in prediction and simulation of exchange rate returns.



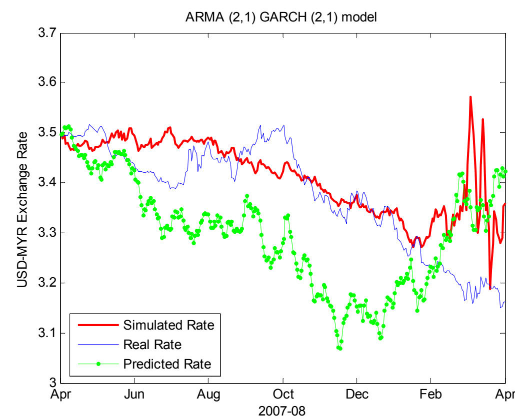


Figure 4.a **Figure 4.b**

Simulation Error 6.063; Prediction Error 0.630 Simulation Error 2.042; Prediction Error 6.664

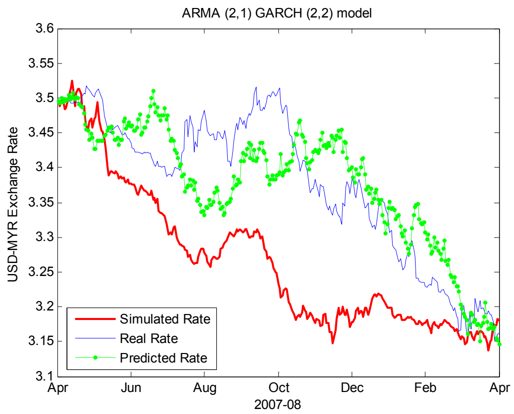
The figures above show the trends of real, simulated and predicted US_{XR} lines. The figure 4.a shows an interesting trend. The simulated line steeply declines in April 2007 itself and goes far below the real US_{XR} line showing substantial divergence. The predicted line closely follows the real US_{XR} line with a narrow gap. The predicted line almost overlaps on the real US_{XR} line. The forecasting is really good. In figure 4.b the simulated line and the real line goes together up to February 2008. Then it shows violent fluctuations. The predicted line goes far below the real US_{XR} line up to February 2008, later it goes up sharply and crosses the real line and goes up further with a wider divergence. The errors increase shapely when the lines diverge from each other. In Figure 4.a the predicted line error is only 0.63 which is the best fit, almost both lines move together in all twelve months.

ARIMA and GARCH lags [2,1, 2,2] and [2,2, 2,2]

Table 5: ARIMA and GARCH parameters for [2,1, 2,2] and [2,2, 2,2] lags.

Mean: ARIMAX(2,1,0); Variance: GARCH(2,2)				Mean: ARIMAX(2,2,0); Variance: GARCH(2,2)			
Parameter	Value	Std Error	't' Value	Parameter	Value	Std Error	't' Value
C	0.000	0.000	-0.652	C	0.000	0.000	-1.547
AR(1)	0.828	0.296	2.794	AR(1)	0.233	0.038	6.170
AR(2)	-0.076	0.078	-0.974	AR(2)	-0.107	0.044	-2.445
MA(1)	-0.792	0.310	-2.552	MA(1)	-0.189	0.034	-5.500
K	0.000	0.000	1.936	MA(2)	0.080	0.039	2.064
GARCH(1)	0.485	0.526	0.923	K	0.000	0.000	1.995
GARCH(2)	0.216	0.437	0.494	GARCH(1)	0.532	0.480	1.109
ARCH(1)	0.069	0.069	1.005	GARCH(2)	0.182	0.408	0.447
ARCH(2)	0.213	0.098	2.187	ARCH(1)	0.061	0.057	1.081
				ARCH(2)	0.206	0.101	2.036

The higher order lags [2,1, 2,2] and [2,2, 2,2] in the ARIMA and GARCH show a few parameters significant that too at lower levels. They are in the range 2.188 and 2.79. In [2,1 2,2] model AR (1), MA (1) and ARCH (2) values are significant. MR (1) shows negative sign. All other parameters in the table 5, section one are insignificant. In the second part of table 5, the 't' values show a higher level of significance for AR (1) , AR (2) and MA (1). AR (2) and MA (1) show negative coefficients. The ARCH (2) coefficient is also significant but with a lower 't' value. The remaining parameters are insignificant. These significant parameters are important and they decide the movement and the trend of the US_{XR}.



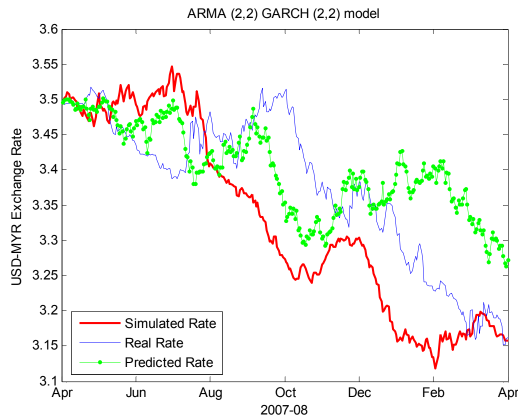


Figure 5.a **Figure 5.b**

Simulation Error 5.385; Prediction Error 1.155 Simulation Error 3.037; Prediction Error 2.190

In figure 5.a the predicted US_{XR} line and the real US_{XR} line both move hand in hand with in a narrow band. But the simulated US_{XR} goes far below the real US_{XR} line exhibiting a wider gap. However all these lines merge together in April, 2008. Figure 5.b shows the US_{XR} lines which exhibit a mixed pattern in higher order lags. The real US_{XR} and the simulated US_{XR} are moving together in trend but with a steady gap and ultimately they touch each other. The predicted rate on the other hand, till November 2007, goes closer to the real US_{XR} line and later it shows an upward movement. The errors are also greater except for the [2,1, 2,2] predicted line. The divergence of simulated line and predicted line from the real line is quantified in terms of squared errors. In the first part of table six the errors are arranged in ascending order in column three. In the second part the same errors are arranged in the ascending order but in column five for easy comparison.

Table 6 Simulation and Prediction divergence squared error

Model	Simulation Error	Prediction Error	Model	Simulation Error	Prediction Error
[2 1 1 2]	6.063	0.630	[1 1 1 1]	1.127	3.093
[2 1 2 2]	5.385	1.155	[2 1 1 1]	1.197	3.002
[0 0 1 1]	2.595	1.673	[1 1 2 1]	2.027	2.611
[1 1 1 2]	3.573	1.917	[2 1 2 1]	2.042	6.664
[1 1 2 2]	2.013	2.277	[2 2 2 2]	3.037	2.190

A closer observation reveals when the AR and ARCH lags are 2 the prediction error is less. The first two models predict the exchange rates well. Similarly in simulation when AR and ARCH lags are one the simulation results are better. These models are to be tested in few other exchange rates to generalize them.

5. Conclusion

The time series forecasting plays a central role in risk management in modern finance. The forecasting of exchange rates etc is vital for hedging decisions. We tried to forecast the US_{XR} by prediction and simulation. Our results indicate that the forecasted exchange rate lines closely follow the trend of the real line. The best fit is given by prediction model in [2,2 1,2] lag and the next best fit is given by simulation model [1,1 1,1]. Overall in all the ten tests conducted, the predicted and simulated exchange rates move in tandem with the real US_{XR}. The declining trend in USD/MYR exchange rate is captured well in all models except two models one in simulation [2,1,2,2] and the other in prediction [2,1,2,1] whose errors are more than six. This lends support to the claim that some financial time series are not entirely random contrary to the predictions of the efficient market hypothesis (Pollock, 2005; Wu, 2001). Ex-post data can be used to achieve fairly accurate forecast that could be used not only in foreign exchange market for hedging but also in share market for buy and sell decisions and in derivative market for hedging and speculative strategies. The above models applied in USD/MYR exchange rate forecasting could easily be applied in other exchange rates also without much alteration in program. In addition the same model could be applied in predicting and simulating share prices and Interbank Offered Yield Rates forecasting. Failing to forecast accurately will lead to suboptimal risk management decision and thereby it may lead to increased cost of hedging or uncovered losses due to improper and mismatched hedging.

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