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*Strictly as per the compliance and regulations of:*

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## I. Introduction

Exchange rate is an important variable which influences decisions taken by the participants of the foreign exchange market, namely investors, importers, exporters, bankers, financial institutions, business, tourists and policy makers both in the developing and developed world as well. Timely forecasting of the exchange rates is able to give important information to the decision makers as well as partakers in the area of the internal finance, buy and sell, and policy making. However, the experimental literature be skeptical about the likelihood of forecasting exchange rates accurately (Dua and Ranjan, 2011). The market where foreign exchange transactions are taken place is the biggest as well the most liquid financial markets. The foreign exchange rate is one of the vital economic indicators in the global monetary markets. For the giant multinational business units, an accurate forecasting of the foreign exchange rates is crucial since it improves their overall profitability (Huang et al., 2004). In the past, the foreign exchange rates were fixed with extremely a small number of short-term variations. Now-a –days, floating foreign exchange rates are prevailed in most of the countries. The recent financial turmoil all over the world demonstrates the urgency of perfect information of the foreign exchange rates (Shim, 2000).

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The series of foreign exchange rate demonstrates a higher volatility, complexity and noise which generate from a mysterious market mechanism producing daily observations (Theodossiou, 1994). Forecasting of a given financial variable is a vital task in the markets where financial transactions are taken place and positively helpful for the stakeholders, namely practitioners; regulators; as well as policy formulators of this market (Pradhan and Kumar, 2010). In the financial as well as managerial decision making process, forecasting is a crucial element (Majhi et al., 2009). Forecasting of the exchange rate is the foremost endeavors for the practitioners and researchers in the spree of international finance, particularly in case of the exchange rate which is floating (Hu et al., 1999). Since the breakdown of Breton-Wood system, prediction of the exchange rate is being more interested. To develop models for forecasting the exchange rates is important in the practical and theoretical aspects. The importance of forecasting the exchange rates in practical aspect is that an accurate forecast can render valuable information to the investors, firms and central banks for in allocation of assets, in hedging risk and in formulating of policy. The theoretical significance of an accurate forecasting exchange rate is that it has vital implications for efficient market hypothesis as well as for developing theoretical model in the field of international finance (Preminger and Franck, 2005). Some corporate tasks that make forecasting the foreign exchange rate so important, namely hedging decision, short-term financing decision, short-term investment decision, capital budgeting decision, earnings assessment and long-term financing decision (Madura, 2006). To forecast exchange rate is a hectic task, but this is an inevitable for taking financial decision in the era of internalization. The significance of the exchange rates' forecasting stems from the reality that the findings of a given financial decision made today is conditional on the exchange rate which will be prevailed in the upcoming period. For this reason forecasting exchange rate is essential for a various international financial transactions, namely speculation, hedging as well as capital budgeting (Moosa, 2008). To understand the movements of exchange rate is a tremendously challenging and essential task. Efforts for deepening our understanding about the movements of exchange rate have taken some approaches. Primarily, efforts concentrated to develop low-frequency basically based experimental models. The aim of model estimation is to present an accurate forecast of exchange rate as well as to get better our understanding the movements of exchange rate. The models could occasionally help to isolate the shortcomings of our knowledge and put forward new way of research (Gradojevic and Yang, 2000). The outcomes of this study render all of the mentioned rationales.

The motivation for this study is to investigate the use of auto regressive (AR) model, when applied to the task of forecasting and trading of the BDT/USD exchange rate using the Bangladesh Bank (BB) fixing series.

## II. Literature Review

The likelihood to capture various patterns in the data as well as improvement of forecasting performance can be enhanced through combining different models. A number of researches are conducted on forecasting and trading financial series by the scholars and they suggest that by combining various models, forecasting accuracy can be enhanced over an individual model.

Khin et al. (2011) state that the economic market model of supply-demand's ex-ante forecast is more perfect and efficient measured either in the context of its statistical decisive factor or by optical immediacy with the actual prices. Pradhan and Kumar ( 2010) conducts a study on Forecasting Exchange Rate in India: An Application of Artificial Neural Network (ANN) Model. and reveal that ANN model is a successful tool for forecasting the exchange rate. Moreover, they reveal that it is possible to extract information concealed in the exchange rate and to predict it into the upcoming. Sermpinis, Dunis and Laws (2010) mention that the Psi and the Genetic Expression perform in the same way and their performance is better among all models in the context of annualized returns and information ratio prior to and following the application of the trading strategy. They also reveal that all models with the exception of ARMA demonstrate an extensive augmentation in their trading performance in the light of annualized return. Dunis and Williams (2003) investigate and analyse regression models' application in trading as well as investment along with the utilization of forecasting foreign exchange rates and trading models. They benchmark NNR models with some other regression based models and different forecasting techniques for determining their prospective added value like a predicting and quantitative trading techniques. To evaluate the forecasting accuracy of the selected models, some statistical measures namely MSE, MPAE, and so on are used as well as they use financial criteria, like returns risk-adjusted reassures. They reveal that regression models, exactly NNR models have the capability for forecasting the EUR/USD exchange rate returns within the sample period and insert value the same as the tool of forecasting and quantitative trading as well. Dunis and Miao ( 2005a) reveal that the adding of the volatility filters include the performance of the models in the respect of annualized return, maximum drawdown, risk –adjusted Sharpe ratio and Calmar ratio. Dunis and Miao (2005b) state that the performance of straightforward carry model is superior to the MACD model in the context of annualized return, risk-adjusted return and maximum potential loss, whilst a collective carry or MACD model contains the least trading volatility, in addition of the two volatility filters puts in noteworthy value to the different three studied modes' performance. Dunis, Laws and Sermpinis (2008a) reveal that two neural network models, namely Higher Order Neural Network (HONN) and Multilayer Perception (MLP) do significantly outperform compared to the other selected models in case of a straightforward trading simulation. After incorporating transaction costs and applying leverage, they also find that same network models beat all other selected models in respect of the annualized return, robust as well as stable result. Dua and Ranjan (2011) do a study on modelling and forecasting the Indian RE/USD exchange, governed by the managed floating foreign exchange rates regime, with vector autoregressive (VAR) and Bayesian vector autoregressive (BVAR) models find that extension of monetary model for incorporating forward premium, capital inflows' volatility as well as order flow is an effective way to improve forecasting accuracy of the selected model. Furthermore, BVAR model usually beat their parallel VAR variants. According to Boero and Marrocu (2002), the performance of linear models is better than non-linear models if concentration is constrained to MSFE. Preminger, and Franck (2005) state that foreign exchange rate forecasting robust models have a tendency for improving Autoregressive and Neural Network model's forecasting accuracy at each time sphere, as well as even of random walk for predictions done at a one-month time - sphere. They also mention that robust models have considerable market timing capability at each forecast horizons. Kamruzzaman and Sarker (2003) mention that the performance of all ANN related models are better than the ARIMA model. Furthermore, they reveal that all the ANN based models are capable to predict the foreign exchange market closely. Bissoondeeal et al. ( 2008) conduct a research for forecasting foreign exchange rates with nonlinear models and linear models and reveal that usually, NN models outperform compared to the time series models which are traditionally applied in forecasting the foreign exchange rates. Philip, Taofiki and Bidemi (2011) compare the performance of two models which are used to forecast the foreign exchange rates, namely Hidden Markov Model and Artificial Neural Network Model and find that the percentage of ANN model's accuracy is more than Hidden Mark Model at 81.2% and 69.9% respectively. Sosvilla-Rivero and

García (2003) do a research for forecasting the USD/EUR exchange rate and evaluate the empirical significance PPP's expectation version for the study purpose. They find that the behavior of the given study's predictors are significant better than the random walk in forecasting the exchange rate up to a five-day period in terms of forecasts error as well as the directional forecast. Dunis and Huang ( 2001) state that the majority trading strategies continue positive returns after incorporating transaction costs. Furthermore, they mention that RNN models come into view as the most excellent sole modeling approach up till now. They also reveal that the model combination that has the most excellent overall performance as per forecasting accuracy, be unsuccessful to upgrade volatility trading outcomes whose basis are RNN. Dunis, Laws, and Sermpinis (2008b) mention that the HONN as well as the MPL networks outperform in predicting the EUR/USD exchange rates fixed up by the ECB until the last part of the year 2007 comparison with the performance of the RNN networks, the ARMA model, the MACD model and the naïve strategy. Panda and Narasimhan (2003) state that NN outperforms the linear AR model in case of in-sample forecasting. Though in case of out-of-sample forecasting, no model is nominated as a better model between the NN and linear AR model, NN can improve the linear AR model in respect of sign forecasting.

## III. Data and Methodology

*a) Data*

Only secondary data related to the daily closing BDT/USD exchange rate is used for the study purpose. The daily closing BDT/USD exchange rate is investigated in this study which is collected from data base Reuters Xtra 3000. The study period is from July 03, 2006 to July 04, 2011 which comprise 1307 trading days. The total data set is broken – down into in-sample data set and out-of-sample data set. The in-sample data set covers the time period from July 03, 2006 to April 30, 2010 and includes 1000 observations and used for the purpose of model estimation and forecasting, whereas out-of-sample covers the time period from May 01, 2010 to July 04, 2011 and contains 307 observations and used for the purpose of forecasting. The in-sample observations and out-of-sample observations are 76.51% and 23.49% respectively in this study.

*b) Jarque-Bera Statistics*

Jarque-Bera statistics is used to test the non-normality of the BDT/USD exchange rate.

*Figure 1 :* BDT/USD Exchange Rate Summary Statistics.

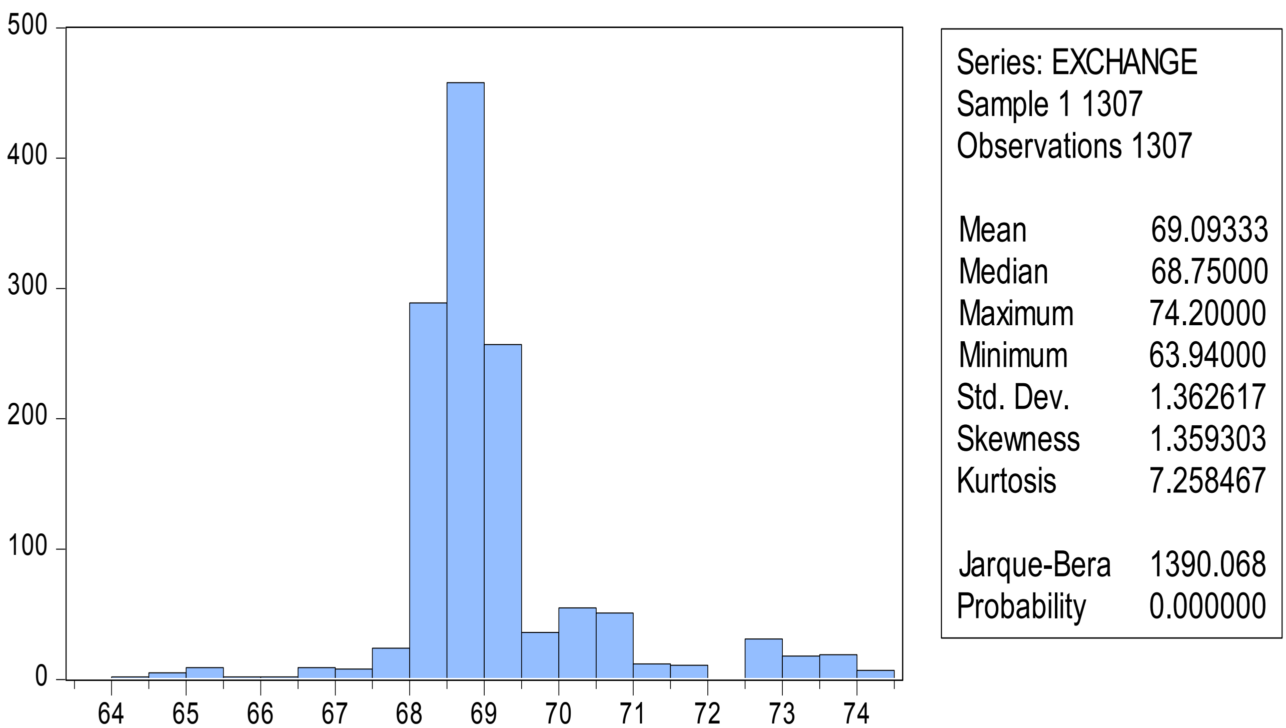


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Figure 1 depicts that the positive skewness, 1.359303, and a high positive kurtosis, 7.258467. According to the Jarque-Bera statistics, the BDT/USD return is non-normal at the confidence interval of 99%, since probability is 0.0000 which is less than 0.01. So, it is required to transform the BDT/USD exchange rate series into the return series.

*c) Transformation of the BDT/USD Exchange Rate Series*

Generally, the movements of the foreign exchange rates are usually non-stationary as well as quite random and not suitable for the study purpose. The series of BDT/USD exchange rates is converted into returns by using the following equation:

$$R_t=\left(\frac{\quad}{_{-1}}\right)-1 \qquad (1)$$

Where,
$R_t$ = the rate of return at time t
$P_t$ = the exchange rate at time t
$P_{t-1}$ = the exchange rate just preceding of the time t

*d) BDT/USD Exchange Rate Returns ADF Test and PP Test*

*Table 1 :* BDT/USD Exchange Rate Returns ADF Test.

| | | t-Statistic | Prob.* |
|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -0.461736 | 0.8959 |
| | 1% level | -3.435165 | |
| | 5% level | -2.863554 | |
| Test critical values: | 10% level | -2.567892 | |

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

Table 1 presents the findings of ADF test and formally confirms that the returns series of the BDT/USD is stationary, since the values of Augmented Dickey-Fuller test statistic, -29.70146, less than its test critical value, – 3.435169 at the level of significance of 1%.

*Table 2 :* BDT/USD Exchange Rate Returns PP Test.

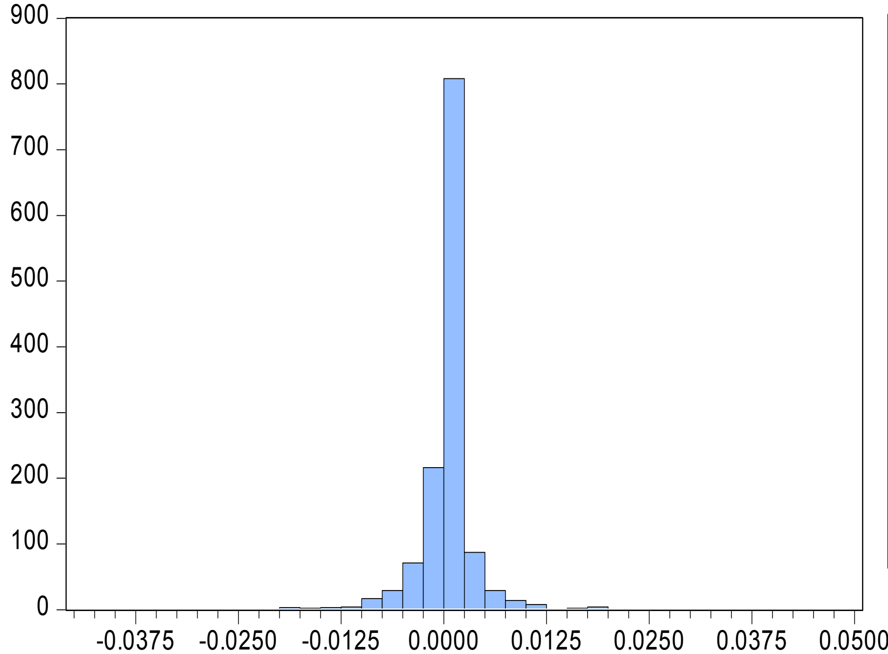
| | | Adj. t-Stat | Prob.* |
|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -1.476719 | 0.5453 |
| | 1% level | -3.435146 | |
| | 5% level | -2.863545 | |
| Test critical values: | 10% level | -2.567887 | |

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

Table 2 demonstrates the findings of the PP test and properly proves that the returns series of the BDT/USD exchange rate is stationary, since the values of PP test statistic, -150.9006, less than its test critical value, -3.435150 at the level of significance of 1%. Therefore, it can be mentioned that the BDT/USD exchange rates returns series is stationary as per both the ADF test as well as PP test.

*e) Summary Statistics of the BDT/USD Exchange Rate Returns*

*Figure 2 :* BDT/USD Exchange Rates Returns Summary Statistics.




Series: RETURN
Sample 1 1307
Observations 1307

| | |
|---|---|
| Mean | 7.62e-05 |
| Median | 0.000000 |
| Maximum | 0.048621 |
| Minimum | -0.044983 |
| Std. Dev. | 0.004159 |
| Skewness | 0.520318 |
| Kurtosis | 41.79787 |
| Jarque-Bera | 82033.72 |
| Probability | 0.000000 |

Figure 2 further disclose a slight positive skewness, 0.520318, and a higher positive kurtosis, 41.79787. According to the Jarque-Bera statistics, the BDT/USD returns series is non-normal at the confidence interval of 99%, since probability is 0.0000 which is less than 0.01.

*f) Specification of the Model*

i. *Benchmark Model*

An autoregressive model and an autoregressive moving average model are benchmarked with a naïve strategy model in this study.

a. *Naïve Strategy*

It takes the most up to date period change as the most excellent forecast of the change which would be occurred in the future (Sermpinis, Dunis, and Laws, 2010). This forecasting model is expressed in the following way:

$$_{t+1} = Y_t \qquad (2)$$

Where

$_{t+1}$ = the forecast rate of return for the next period
$Y_t$ = the actual rate of return at period t

The performance of the naïve strategy is appraised in the context of the trading performance by the way of a simulated trading strategy.

ii. *Autoregressive Model*

According to autoregressive model, a forecast is a function of previous values of the time series (Hanke and Wichern, 2009). This model takes the following equation:

$$y_t=\mu+\varphi_1 y_{t-1}+\varphi_2 y_{t-2}+\cdots+\varphi_p y_{t-p}+u_t \qquad (3)$$

Where,
$Y_t$ = the actual rate of return at period t
$M$ = constant
$\Phi$ = co-efficient
$u_t$ = a white noise disturbance term

iii. *Autoregressive Moving Average Model*

This model represents the present value of a time series depends upon it past values which is the autoregressive component and on the preceding residual values which is the moving average component (Sermpinis, Dunis and Laws, 2010). The ARMA (p,q) model has the following general form:

$$Yt = \varphi_0 + \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \cdots + \varphi_p Y_{t-p} + \varepsilon_t - w_1\varepsilon_{t-1} - w_2\varepsilon_{t-2} - \cdots - w_q\varepsilon_{t-q} \qquad (4)$$

Where,
$Y_t$ = the dependent variable at time t
$Y_{t-1}$, $Y_{t-2}$, and $Y_{t-p}$ = the lagged dependent variables
$\varphi_0$, $\varphi_1$, $\varphi_2$, and $\varphi_p$ = regression coefficients
$\varepsilon_t$ = the residual term
$\varepsilon_{t-1}$, $\varepsilon_{t-2}$, and $\varepsilon_{t-p}$ = previous values of the residual
$w_1$, $w_2$, and $w_q$ = weights

*g) Statistical and Trading Performance of the Model*

i. *Measures of the Statistical Performance of the Model*

The statistical performance measures are, namely mean absolute error (MAE); mean absolute percentage error (MAPE); root mean squared error (RMSE); and theil-u, are used to select the best model in the in-sample case and the out-of-sample case individually in this study. For all four of the error statistics retained (RMSE, MAE, MAPE and Theil-U) the lower the output, the better the forecasting accuracy of the model concerned.

ii. *Measures of the Trading Performance of the Model*

The trading performance measures, like annualized return ( ); annualized volatility( ); information ratio (SR); and maximum drawdown (MD), are used to select the best model. That model's trading performance would be the best whose annualized return, cumulative return, ratio information is the highest, and on the other hand whose annualized volatility and maximum drawdown would be the lowest.

## IV. Empirical Results and Discussion

### a) *Model Estimation*

i. *AR(1) Model*

The table below shows the output of the AR (1) BDT/USD returns estimation:

*Table 3 :* Output of the AR (1) BDT/USD Returns Estimation.

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 2.49E-05 | 0.000107 | 0.231425 | 0.8170 |
| AR(1) | -0.283663 | 0.030369 | -9.340439 | 0.0000 |

The estimated AR (1) model takes the following form:

$$R_t = 0.0000249 - 0.283663 R_{t-1} \qquad (5)$$

The coefficient (with the exception of the constant) of the estimated AR (1) is significant at the confidence interval of 95% (equation AR (1), since the probability of its coefficient (except the constant) is less than 0.05.

ii. *ARMA (1, 1) Model*

The following table shows the output of the ARMA (1,1) BDT/USD returns estimation:

*Table 4 :* Output of the ARMA (1,1) BDT/USD Returns Estimation.

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 1.45E-05 | 8.29E-05 | 0.174879 | 0.8612 |
| AR(1) | 0.185091 | 0.086714 | 2.134494 | 0.0330 |
| MA(1) | -0.505725 | 0.076194 | -6.637337 | 0.0000 |

The estimated ARMA (1, 1) model takes the following form:

$$R_t = 0.0000145 + 0.185091 Y_{t-1} - 0.505725 Y_{t-2} \qquad (6)$$

The all coefficients (with the exception of the constant) of the estimated ARMA (1, 1) model are significant at the confidence interval of 95%, since the probability of its each coefficient (except the constant) is less than 0.05.

### b) *Statistical Performance*

i. *In -Sample Statistical Performance*

The following table presents the comparison of the in-sample statistical performance results of the selected models.

*Table 5 :* In -Sample Statistical Performance Results.

| Particulars | Naive Strategy | ARMA (1,1) | AR(1) |
|---|---|---|---|
| Mean Absolute Error | 0.0033 | **0.0019** | **0.0019** |
| Mean Absolute Percentage Error | 107.76% | 58.35% | **58.04%** |
| Root Mean Squared Error | 0.0073 | **0.0043** | 0.0044 |
| Theil's Inequality Coefficient | 0.8011 | **0.7241** | 0.7470 |

Table 5 reveals that both the ARMA(1,1) and AR(1) models have the same and the lowest mean absolute error (MAE) at 0.0019, whereas naïve strategy has the lowest MAE at 0.0033. The AR (1) model has the lowest mean absolute percentage error (MAPE) at 58.04% followed by the ARMA (1,1) model; and naïve strategy at 58.35%; and 107.76% respectively. The ARMA(1,1) model has the lowest root mean squared error (RMSE) at 0.0043, whereas the AR(1) model has the second lowest RMSE at 0.0044 followed by the naïve strategy at 0.0073. Therefore, the ARMA (1,1) model is the best performing model on the basis of in- sample - statistical performance results, since this model is nominated as the best model three times, whereas the AR(1) model is nominated as the best model twice and the naïve strategy model is nominated as the best model not a single time.

ii. *Out – Of- Sample Statistical Performance*

The following table demonstrates the comparison of the out-of-sample statistical performance results of the selected models.

*Table 6 :* Out –of - Sample Statistical Performance Results.

| Particulars | Naive Strategy | ARMA (1,1) | AR(1) |
|---|---|---|---|
| Mean Absolute Error | 0.0022 | **0.0013** | **0.0013** |
| Mean Absolute Percentage Error | 94.31% | 59.12% | **53.64%** |
| Root Mean Squared Error | 0.0041 | **0.0024** | **0.0024** |
| Theil's Inequality Coefficient | 0.8109 | **0.7192** | 0.7391 |

Table 6 reveals that both the ARMA (1,1) and the AR(1) models have the same and the lowest mean absolute error (MAE) at 0.0013, whereas naïve strategy has the second lowest at 0.0022. The AR (1) model has the lowest mean absolute percentage error (MAPE) at 53.64% followed by the ARMA (1,1) and the naïve strategy models at 59.12%; and 94.31% respectively. Both the ARMA (1,1) and the AR(1) models have the same and the lowest root mean squared error (RMSE) at 0.0024, whereas the naïve strategy has the second lowest at 0.0041. The ARMA(1,1) model has the lowest theil's inequality coefficient at 0.7192 followed by the AR(1) model; and the naïve strategy at 0.7391; and 0.8109 respectively. Therefore, both the ARMA (1,1) and AR(1) model are the best performing model on the basis of out –of - sample statistical performance results, since these two models are nominated as the best model three times, whereas the the naïve strategy model is nominated as the best model not a single time.

c. *Trading Performance*

i. *In-Sample Trading Performance*

The following table shows the comparison of the in-sample trading performance results of the selected models.

*Table 7 :* In- Sample Trading Performance Results.

| Particulars | Naive Strategy | ARMA(1,1) | AR (1) |
|---|---|---|---|
| Annualised Return | -11.59% | **23.38%** | 13.39% |
| Annualised Volatility | **6.19%** | 7.06% | 7.16% |
| Sharpe Ratio | -1.87 | **3.31** | 1.87 |
| Maximum Drawdown | **-48.91%** | -5.26% | -6.18% |

Table 7 reveals that the ARMA (1,1) model has the highest annualized return at 23.38% . The naïve strategy has the lowest annualized volatility at 6.19%. In addition, ARMA (1,1) model has the highest Sharpe ratio at 3.31. The naïve strategy model has the lowest downside risk as measured by maximum drawdown at -48.91%. Therefore, both the naïve strategy and ARMA (1,1) models might be selected as the overall best model in – sample trading performance, since these models are nominated as the best models the highest times.

ii. *Out-Of-Sample Trading Performance*

The following table demonstrates the comparisons of the out-of-sample trading performance results of the selected models.

*Table 8 :* Validation Trading Performance Results.

| Particulars | Naive Strategy | ARMA(1,1) | AR (1) |
|---|---|---|---|
| Annualised Return | -8.96% | 13.54% | **14.49%** |
| Annualised Volatility | **2.89%** | 3.94% | 3.93% |
| Sharpe Ratio | -3.10 | 3.44 | **3.69** |
| Maximum Drawdown | **-10.92%** | -1.11% | -1.28% |

Table 8 depicts that the AR(1) model has the highest annualised return at 14.49%, whereas the naïve strategy model has the lowest annualised volatility at 2.89%. Moreover, the AR(1) model has the highest Sharpe ratio at 3.69. The naïve strategy model has the lowest downside risk as measured by maximum drawdown at -10.92%. On the basis of the discussion of the table 10, both the AR(1) and naïve strategy models are selected as the overall best model out-of – sample trading performance, since it is nominated as the best model the highest times.

## V. Conclusion

Techniques of forecasting foreign exchange rates depend upon the efficient market hypothesis are the shortcomings and in the real world, market inefficiencies are existed. However, foreign exchange markets are comparatively efficient and the opportunity to hold a strategy for making abnormal return is reduced (Dunis and Williams, 2003). The average Sharpe ratio of the foreign exchange managed future industry is merely 0.80 and for running a profitable foreign exchange trading desk, more than 60% winning trades is needed (Grabbe, 1996 ). Moreover, the Sharpe ratio of all models except the naive strategy is more than 0.80 in case of in-sample trading performance outcomes and the ARMA (1,1) model has the highest at 3.85. On the other hand, the Sharpe ratio of both the ARMA (1,1) model and the AR (1) model are more than 0.80, whereas the naive strategy model are less than 0.80 and the AR (1) model has the highest at 3.69 in case of the validation trading performance results (out-of-sample).

On the basis of the overall findings of this study, it can be concluded that in case of in-sample the ARMA (1,1) model, whereas both the ARMA (1,1) and AR(1) models are capable to add value significantly to the forecasting and trading BDT/USD exchange rate in the context of statistical performance measures. On the other hand, the naive strategy and ARMA (1,1) models in case of in-sample, whereas both the AR(1) and naive strategy models in case of out-of-sample can add value significantly for forecasting and trading BDT/USD exchange rate on the basis of trading performance.

In this study, only two models, namely an AR model and an ARMA model are benchmarked only with a naive strategy model. The naive strategy model is merely evaluated in the context of the trading performance. Some limitations are reflected in case of the estimated models, namely the estimated ARMA (1,1), and AR(1) models are not normally distributed, serial correlation of the residuals of the estimated ARMA (1,1) and AR(1) models is present, and the variances of the estimated ARMA (1,1), and AR(1) models are not constant. Appropriate transformation of the original model, application of the Newey–West method, and changing the data frequency or using the generalized least squares method can be considered to overcome the indentified shortcomings.

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# Appendices

## A.1 EViews7 Output of ADF Test.

Null Hypothesis: EXCHANGE has a unit root
Exogenous: Constant
Lag Length: 5 (Fixed)

| | | t-Statistic | Prob.* |
|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -0.461736 | 0.8959 |
| Test critical values: | 1% level | -3.435165 | |
| | 5% level | -2.863554 | |
| | 10% level | -2.567892 | |

*MacKinnon (1996) one-sided p-values.
Augmented Dickey-Fuller Test Equation
Dependent Variable: D(EXCHANGE)
Method: Least Squares
Date: 08/26/11 Time: 11:43
Sample (adjusted): 7 1307
Included observations: 1301 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| EXCHANGE(-1) | -0.002550 | 0.005523 | -0.461736 | 0.6443 |
| D(EXCHANGE(-1)) | -0.301776 | 0.028276 | -10.67240 | 0.0000 |
| D(EXCHANGE(-2)) | -0.122482 | 0.028979 | -4.226588 | 0.0000 |
| D(EXCHANGE(-3)) | -0.062716 | 0.029095 | -2.155555 | 0.0313 |
| D(EXCHANGE(-4)) | -0.174358 | 0.028656 | -6.084534 | 0.0000 |
| D(EXCHANGE(-5)) | 0.013938 | 0.027287 | 0.510791 | 0.6096 |
| C | 0.183619 | 0.381572 | 0.481218 | 0.6304 |

| | | | |
|---|---|---|---|
| R-squared | 0.116949 | Mean dependent var | 0.004681 |
| Adjusted R-squared | 0.112855 | S.D. dependent var | 0.277839 |
| S.E. of regression | 0.261692 | Akaike info criterion | 0.162069 |
| Sum squared resid | 88.61660 | Schwarz criterion | 0.189891 |
| Log likelihood | -98.42575 | Hannan-Quinn criter. | 0.172507 |
| F-statistic | 28.56242 | Durbin-Watson stat | 1.997549 |
| Prob(F-statistic) | 0.000000 | | |

## A.2 EViews7 Output of PP Test.

Null Hypothesis: EXCHANGE has a unit root
Exogenous: Constant
Bandwidth: 5 (Used-specified) using Bartlett kernel

| | | Adj. t-Stat | Prob.* |
|---|---|---|---|
| Phillips-Perron test statistic | | -1.476719 | 0.5453 |
| Test critical values: | 1% level | -3.435146 | |
| | 5% level | -2.863545 | |
| | 10% level | -2.567887 | |

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

| | |
|---|---|
| Residual variance (no correction) | 0.081308 |
| HAC corrected variance (Bartlett kernel) | 0.040913 |

Phillips-Perron Test Equation
Dependent Variable: D(EXCHANGE)
Method: Least Squares
Date: 08/26/11 Time: 11:46
Sample (adjusted): 2 1307
Included observations: 1306 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| EXCHANGE(-1) | -0.017108 | 0.005826 | -2.936312 | 0.0034 |
| C | 1.186782 | 0.402624 | 2.947614 | 0.0033 |

| | | | |
|---|---|---|---|
| R-squared | 0.006568 | Mean dependent var | 0.004778 |
| Adjusted R-squared | 0.005807 | S.D. dependent var | 0.286197 |
| S.E. of regression | 0.285365 | Akaike info criterion | 0.331435 |
| Sum squared resid | 106.1889 | Schwarz criterion | 0.339359 |
| Log likelihood | -214.4270 | Hannan-Quinn criter. | 0.334408 |
| F-statistic | 8.621929 | Durbin-Watson stat | 2.531255 |
| Prob(F-statistic) | 0.003380 | | |

A.3 EViews7 Output of AR(1) Model

Dependent Variable: RETURN
Method: Least Squares
Date: 08/26/11 Time: 12:28
Sample (adjusted): 2 1000
Included observations: 999 after adjustments
Convergence achieved after 3 iterations

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 2.49E-05 | 0.000107 | 0.231425 | 0.8170 |
| AR(1) | -0.283663 | 0.030369 | -9.340439 | 0.0000 |

| | | | |
|---|---|---|---|
| R-squared | 0.080465 | Mean dependent var | 2.48E-05 |
| Adjusted R-squared | 0.079543 | S.D. dependent var | 0.004546 |
| S.E. of regression | 0.004361 | Akaike info criterion | -8.030117 |
| Sum squared resid | 0.018963 | Schwarz criterion | -8.020294 |
| Log likelihood | 4013.044 | Hannan-Quinn criter. | -8.026384 |
| F-statistic | 87.24379 | Durbin-Watson stat | 2.019434 |
| Prob(F-statistic) | 0.000000 | | |
| Inverted AR Roots | -.28 | | |

A.4 EViews7 Output of ARMA(1,1) Model

Dependent Variable: RETURN
Method: Least Squares
Date: 09/07/11 Time: 11:38
Sample (adjusted): 2 1000
Included observations: 999 after adjustments
Convergence achieved after 6 iterations
MA Backcast: 1

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 1.45E-05 | 8.29E-05 | 0.174879 | 0.8612 |
| AR(1) | 0.185091 | 0.086714 | 2.134494 | 0.0330 |
| MA(1) | -0.505725 | 0.076194 | -6.637337 | 0.0000 |

| | | | |
|---|---|---|---|
| R-squared | 0.099899 | Mean dependent var | 2.48E-05 |
| Adjusted R-squared | 0.098092 | S.D. dependent var | 0.004546 |
| S.E. of regression | 0.004317 | Akaike info criterion | -8.049476 |
| Sum squared resid | 0.018563 | Schwarz criterion | -8.034741 |
| Log likelihood | 4023.713 | Hannan-Quinn criter. | -8.043876 |
| F-statistic | 55.27131 | Durbin-Watson stat | 1.973859 |
| Prob(F-statistic) | 0.000000 | | |

| | |
|---|---|
| Inverted AR Roots | .19 |
| Inverted MA Roots | .51 |