Forecasting the NTD/USD Exchange Rate using Autoregressive Model

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Abstract

The key motivation of this study is to examine the application of autoregressive model for forecasting and trading the NTD/USD exchange rates from July 03, 2006 to April 30, 2008 as in-sample and May 01, 2008 to July 04, 2009 as out of sample data set. AR and ARMA models are benchmarked with a naïve strategy model. The major findings of this study is that in case of in-sample data set, the ARMA model, whereas in case of out-of-sample data set, both the ARMA and AR models jointly outperform other models for forecasting the NTD/USD exchange rate respectively in the context of statistical performance measures. As per trading performance, both the ARMA and naive strategy models outperform all other models in case of in-sample data set. On the other hand, both the AR and naive strategy models do better than all other models in case of out-of-sample data sets as per trading performance.

I. Introduction

Since an exchange rate is the relative price of one nation's money in term of the money of another nation, it is natural to think of an exchange rate as determined, at least proximately, by the outstanding stocks of these monies and by the demands to hold these stocks (Mussa, 1984). 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 (Alama, 2012). Recently, peculators often deliberately accept a net open position in foreign exchange. Speculation probably occurs in the spot or in the forward markets, although a pure speculation is regarded as being confined to the forward market because little or no funds are required. Besides, sometimes market can not take the accuracy of foreign exchange rate well however it is very vital indicator of determining the economics of a country especially for the market actors. 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).

Almost people are familiar with the nominal exchange rate or the term of exchange rate that is the price of one currency in terms of another. Considering the theories of exchange rate determination discussed so far, we might believe that with all this knowledge, experts should be quite adept at forecasting future exchange rates. In fact, forecasting future spot exchange rates is difficult. Although researchers have shown the theories we have covered to be relevant in terms of explaining systematic patterns of exchange rate behavior, the usefulness of these theories for predicting future exchange rates is limited by the propensity for the unexpected to occur. Since the breakdown of the Bretton Woods system of fixed exchange rates in the early 1970s, forecasting currency values has become crucial for many purposes such as international comparisons of incomes, earnings and the costs of living by international agencies, management and alignment of exchange rates by governments, and corporate financial decision making. 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. It is influenced by many correlated political view, economic and psychological factors. 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.

In the exchange-rate forecasting literature, the paper by Meese and Rogoff (1983) remains highly influential as it demonstrates that structural models are unable to outperform the random walk model, which simply predicts that the exchange rate would not change at all. 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 NTD/USD exchange rate using the Taiwan bank data fixing series.

II. Literature Review

Some authors have stressed that the poor forecasting performance of fundamental-based models is not related to the weak informative power of fundamentals. The superiority of random-walk forecasts is instead related to the weakness of the econometric techniques used in producing out-of-sample forecasts (Taylor and Peel, 2000 in Altavilla and Grauwe, 2006). The present study contributes to the ongoing debate regarding the possibility of correctly forecasting future exchange rate movements. The econometric evidence resulting from this kind of study can suggest which model should be adopted in order to achieve a better forecasting performance. A common characteristic of much of the existing studies is their focus on either linear or non-linear models (Altavilla and Grauwe, 2006).

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. While Lam et al examined that in terms of the exchange-rate predictability, empirical results suggest that the PPP model, UIP model and SP model are in general able to outperform the random-walk model as well as the historical average return for the forecast of the exchanges rates. The other researchers namely Altavilla and Grauwe stressed that nonlinear models with more elaborate mean-reverting components dominate at longer horizons especially when deviations from long-term equilibrium are large they found out that the results also suggest that combining different forecasting procedures generally produces more accurate forecasts than can be attained from a single model. 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. On the other side Li et al (2007) studied the application of RLS-TS model to GBP/USD Exchange Rate forecasting. They found out that RLS-TS performs better than random walk, linear regression, auto regression integrated moving average, and artificial neural network model in predicting GBP/USD currency exchange rates. It is very interesting result more over they stated that a grid search is used to choose the optimal parameters. Howrey (1994) stated in his research entitled “Exchange rate forecasts with the Michigan Quarterly Econometric Model of the US economy” that when the Michigan Quarterly Econometric Model is used, it is found that ex post out-of-sample forecasts of the trade-weighted value of the US dollar produced by the model are also superior to forecasts of a random-walk model. However, ex ante forecasts in which all the exogenous as well as the endogenous variables are forecast are less accurate than those produced by the random walk. The price of imported goods in foreign currency, an exogenous variable in both the Michigan and Italian econometric models, is the key variable in the Michigan model which explains the divergence of the ex-ante and ex post forecasting results. The other interesting study comes from Kamruzzamana and Sarkerb (2003) entitled “Comparing ANN Based Models with ARIMA for Prediction of Forex Rates”. In their study, they developed and investigated three Artificial Neural Network (ANN) based forecasting models using Standard Backpropagation (SBP), Scaled Conjugate Gradient (SCG) and Backpropagation with Baysian Regularization (BPR) for Australian Foreign Exchange to predict six different currencies against Australian dollar. They used five moving average technical indicators to build the models. All the ANN based models outperform ARIMA model. They found that SCG based model performs best when measured on the two most commonly used metrics and shows competitive results when compared with BPR based model on the third indicator. Their experimental results demonstrate that ANN based model can closely forecast the forex market. While the research with title “Forecasting the exchange rate in South Africa: A comparative analysis challenging the random walk Model” conducted by Botha and Pretorius (2009) reveal that the multivariate models (VARMA) outperformed the univariate models (except for the Random walk model) in the short-run forecasts, one step ahead, while the multivariate models, performed better in the longer-run forecasts. To improve the accuracy of especially the multivariate models, they recommended that multiple frequencies be used to capture the dynamic behavior between variables in a Structural VAR framework. In their study the two approaches to exchange rate forecasting – the technical and fundamental approach had compared. Various univariate time series models, including the random walk model, was compared to various multivariate time series models (using the MAD/mean ratio). Ghalayini (2013) conducted the research entitled “Modeling and Forecasting the US Dollar/Euro Exchange Rate” to investigate the sustainability of basic exchange rate theory and to construct econometric models capable to generate consistent and rational forecasts for the dollar/euro exchange rate and the result is the specifications of an economic model for dollar/euro exchange rate as well the estimation of the model in The Vector Error Correction Model form. The model that they developed in their study consider in addition to the two variables proposed by basic theories, two other variables, one variable representing the Money Aggregates, and one variable representing the Business Cycles. 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) stated 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. Furthermore, Rout et al (2013) with their research entitled “Forecasting of currency exchange rates using an adaptive ARMA model with differential evolution based training” also reveal that the proposed model that is suitably ARMA and differential evolution (DE) based training of its feed-forward and feed-back parameters offers the best performance for predicting exchange rates compared to those offered by other three similar models studied. They tried to developed model which were compared with other four competitive methods such as ARMA-particle swarm optimization (PSO), ARMA-cat swarm optimization (CSO), ARMA-bacterial foraging optimization (BFO) and ARMA-forward backward least mean square (FBLMS).

III. Data and Methodology

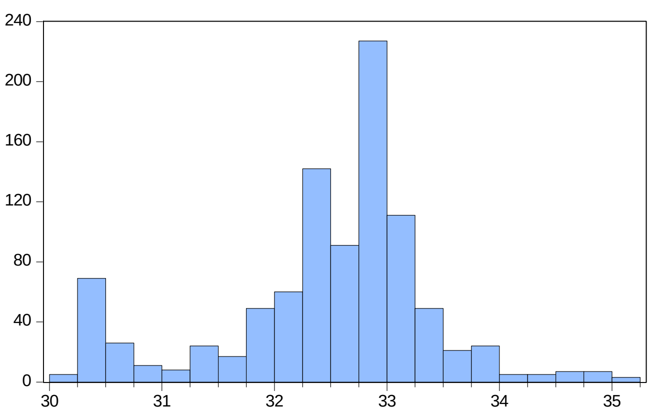
a. Data

In this study, the only data that had been used is the secondary data related to the daily closing NTD/USD exchange rate is used for the study purpose. The daily closing NTD/USD exchange rate is investigated in this study which is collected from data base of Taiwan Bank. The study period is from July 03, 2006 to July 04, 2009 which consist of 961 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, 2008, whereas out-of-sample covers the time period from May 01, 2008 to July 04, 2009.

b. Jarque-Bera Statistics

Jarque-Bera statistics is a goodness-of-fit test of whether sample data have the skewness and kurtosis matching a normal distribution, in other words it is used to test the non-normality of the NTD/USD exchange rate

Figure 1. NTD/USD Exchange Rate Summary Statistics.



Series: EXCHANGE	
Sample 7/03/2006 7/04/2011	
Observations 961	
Mean	32.46625
Median	32.68700
Maximum	35.17400
Minimum	30.01000
Std. Dev.	0.938613
Skewness	-0.653803
Kurtosis	3.647770
Jarque-Bera	85.26635
Probability	0.000000

Figure 1 depicts that the positive skewness, -0.6538, and a high positive kurtosis, 3.6477. According to the Jarque-Bera statistics, the NTD/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 NTD/USD exchange rate series into the return series.

c. Transformation of the NTD/USD Exchange Rate Series

Due to the probability of exchange rate summary statistics which is 0.0000 (less than 0.01) so, it is required to transform the NTD/USD exchange rate series into the return 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 NTD/USD exchange rates is converted into returns by using the following equation:

$$R_t = \frac{P_t}{P_{t-1}} - 1$$

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. NTD/USD Exchange Rate Returns ADF Test and PP Test

An augmented Dickey–Fuller test (ADF) is a test for a unit root in a time series sample. It used in the test, is a negative number while PP (Phillips-Perron test statistic) is used in time series analysis to test the null hypothesis that a time series is integrated of order 1. To account for this, the augmented Dickey–Fuller test's regression includes lags of the first differences of yt and this test involves fitting (1), and the results are used to calculate the test statistics. And here is the outcome of NTD/USD exchange rate returns using ADF test.

Table 1. NTD/USD Exchange Rate Returns ADF Test

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.379418	0.5936
Test critical values:	1% level	-3.436948	
	5% level	-2.864342	
	10% level	-2.568314	

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

Table 1 presents the findings of ADF test and formally confirms that the returns series of the NTD/USD is stationary, since the values of Augmented Dickey- Fuller test statistic is less than its test critical value, – 3.436948 at the level of significance of 1%.

And here is the outcome of NTD/USD exchange rate returns using PP test.

Table 2. NTD/USD Exchange Rate Returns PP Test.

	Adj. t-Stat	**Prob.***
Phillips-Perron test statistic	-1.431473	0.5679

Test critical values:	1% level	-3.436941
	5% level	-2.864339
	10% level	-2.568313

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

Table 2 demonstrates the findings of the PP test and properly proves that the returns series of the NTD/USD exchange rate is stationary, since the values of PP test statistic is less than its test critical value, -3.436941 at the level of significance of 1%.

Therefore, it can be mentioned that the NTD/USD exchange rates returns series is stationary as per both the ADF test as well as PP test.

e. Summary Statistics of the NTD/USD Exchange Rate Returns

Figure 2. Summary Statistics of the NTD/USD Exchange Rate Returns

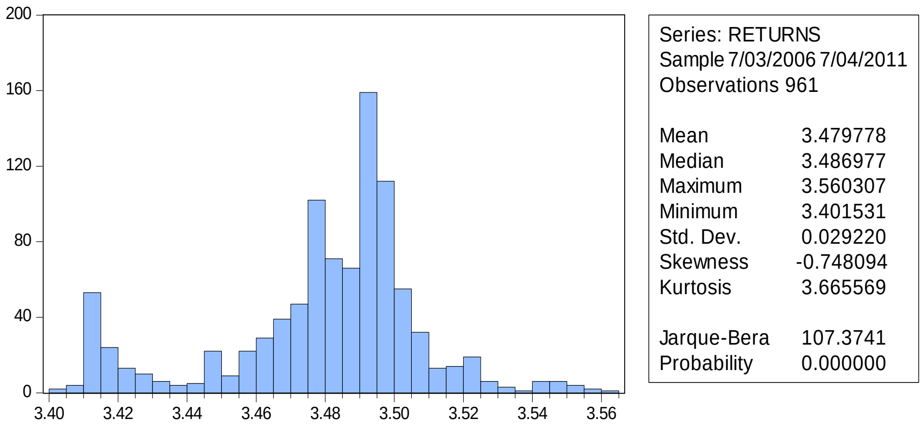


Figure 2 further disclose a slight negative skewness, -0.748094, and a higher positive kurtosis, 3.665569. According to the Jarque-Bera statistics, the NTD/USD returns series is non-normal at the confidence interval of 99%, since probability is 0.0000 which is less than 0.01.

f. Specification of the Model

1) Benchmark Model (Naïve Strategy)

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

Naïve forecast is the most cost-effective forecasting model, and provide a benchmark against which more sophisticated models can be compared. 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:

$$\mathrm{t} + 1 = Y_t$$

Where

$\mathrm{t} + 1$ = 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.

2) Autoregressive Model

Autoregressive models are remarkably flexible at handling a wide range of different time series patterns. The autoregressive model is one of a group of linear prediction formulas that attempt to predict an output y[n] of a system based on the previous outputs (y[n-1],y[n-2]...) and inputs (x[n], x[n-1], x[n-2]...).

This model takes the following equation:

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

Where,

y_t = the actual rate of return at period t

u_t = a white noise disturbance term

3) Autoregresive moving average

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:

$$Y_t = \varphi_0 + \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \cdots + \varphi_p Y_{t-p} + \varepsilon_t - w_1 \varepsilon_{t-1} - w_2 \varepsilon_{t-2} - \cdots + w_p \varepsilon_{t-p}$$

Where:

Y_t = the dependent variable at time t

$Y_{t-1}, Y_{t-2}, \ldots, and\ Y_{t-p}$ = the lagged dependent variables

$\varphi_0, \varphi_1, \varphi_2, \ldots, and\ \varphi_p$ = regression coefficients

ε_t = the residual term

$\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots, and\ \varepsilon_{t-p}$ = previous values of the residual

$w_1, w_2, \ldots, and\ w_p$ = weights

g. Statistical and Trading Performance of the Model

1. Measures of the Statistical Performance of the

Statistical performance is the report of measurement Statistical Performance of the model In order to compare predictions from a model and observations measurements whereby several statistical performances measures can be used. 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.

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

Trading performance is the accomplishment of a given task in a commerce and market financial transaction measured against preset known standards of accuracy, completeness, cost, and speed. In this study, the trading performance like annualized return (AR); annualized volatility(AV); 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 Result and Discussion

a. Model estimation

1) *AR(1) Model*

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

Table 3. Output of the AR (1) NTD/USD Returns Estimation

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3.540925	0.143069	24.74977	0.0000
AR(1)	1.160206	0.045384	25.56428	0.0000

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.

2) *ARMA (1, 1) Model*

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

Table 4. Output of the ARMA (1) NTD/USD Returns Estimation

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3.540925	3.356732	20.896347	0.0018
AR(1)	2.020106	0.085014	32.96017	0.0147
MA (1)	-0.158513	0.045666	-3.471124	0.0006

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

1). 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	0.0013	0.0008	0.0009
Mean Absolute Percentage Error	87.85%	58.35%	58.35%
Root Mean Squared Error	0.0041	0.0035	0.0032
Theil's Inequality Coefficient	0.4091	0.2001	0.2783

Table 5 reveals that the ARMA(1,1) has the lowest mean absolute error (MAE) than AR(1) and naïve Strategy at 0.0008, whereas AR(1) has the second lowest MAE at 0.0009. The Naïve strategy has the last lowest MAE at 0.0013. Both the ARMA(1,1) and AR(1) models have the same and the lowest mean absolute percentage error (MAPE) at 58.35%, whereas naïve strategy has the lowest MAPE at 87.85%. The AR(1) model has the lowest root mean squared error (RMSE) at 0.0032, whereas the ARMA(1,1) model has the second lowest RMSE at 0.0035 followed by the naïve strategy at 0.0041. The ARMA(1,1) model has the lowest theil's inequality coefficient at

0.2001 followed by the AR(1) model; and the naïve strategy at 0.2783; and 0.4091 respectively. **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.

2). 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	0.0009	0.0002	0.0002
Mean Absolute Percentage Error	68.26%	60.01%	56.35%
Root Mean Squared Error	0.0021	0.0016	0.0018
Theil's Inequality Coefficient	0.4001	0.0909	0.1992

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 0.0002, whereas naïve strategy has the second lowest at 0.0009. The AR (1) model has the lowest mean absolute percentage error (MAPE) at 56.35% followed by the ARMA (1,1) and the naïve strategy models at 60.01%; and 68.26% respectively. ARMA (1,1) model has the lowest root mean squared error (RMSE) at 0.0016, whereas the AR (1) has the second lowest at 0.0018 and the third lowest of RMSE is Naïve strategy at 0.0021. The ARMA(1,1) model has the lowest theil's inequality coefficient at 0.0909 followed by the AR(1) model; and the naïve strategy at 0.1992; and 0.4001 respectively. **Therefore**, the ARMA (1,1) model is the best performing model on the basis of out- 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.

c. Trading Performance

1). 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)**
Annualized Return	-5.63%	11.05%	8.32%
Annualized Volatility	4.23%	5.06%	5.02%
Sharpe Ratio	-4.20%	1.01%	-2.05%
Maximum Drawdown	-87.50%	-12.87%	-23.99%

Table 7 reveals that the ARMA (1,1) model has the highest annualized return at 11.05% . The naïve strategy has the lowest annualized volatility at 4.23%. In addition, ARMA (1,1) model has the highest Sharpe ratio at 1.01%. The naïve strategy model has the lowest downside risk as measured by maximum drawdown at – 87.50%. **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.

2. 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)**
Annualized Return	-28.65%	6.45%	6.50%
Annualized Volatility	1.05%	1.07%	1.02%
Sharpe Ratio	-8.10%	1.02%	1.01%
Maximum Drawdown	-35.20%	-0.04%	-1.24%

Table 8 depicts that the AR(1) model has the highest annualized return at 6.50%, whereas the naïve strategy model has the lowest annualized volatility at -28.65%. Moreover, the ARMA(1,1) model has the highest Sharpe ratio at 1.02%. The naïve strategy model has the lowest downside risk as measured by maximum drawdown at -35.20%. On the basis of the discussion, 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). 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 NTD/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 naïve strategy models in case of out-of-sample can add value significantly for forecasting and trading NTD/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 identified shortcomings.

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