AN APPLICATION OF FOUR FOREIGN CURRENCY FORECASTING MODELS TO THE U.S. DOLLAR AND MEXICAN PESO

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I. INTRODUCTION

Global investors, banks and non-bank financial institutions, central banks, and portfolio managers are all interested in finding a model to accurately determine future exchange rates. The accuracy of exchange rate forecasts is critical for a variety of financial decisions made by Multinational Corporations (MNCs) in relations to hedging exchange risk exposure, developing arbitrage opportunities, and making investment and financial decisions. According to Czinkota et. al. (1996) growth in foreign currency trading has been nothing less than astronomical. In April 1992 the daily foreign currency trading on world markets exceeded \$1.6 trillion. The daily volume of the trade is more than many times the daily turnover of all U.S. bonds and stocks combined.

The forecasting power of currency exchange rate models has received considerable attention because of the sheer size of the currency market and growth global trade and investment. The importance of this study stems from several observations. First, the recent two decades have been characterized by growing integration of the American and Mexican economies. Second, as seen over the past several years, the default on debt payments by the Mexican government has had major impacts on the banking industry and the U.S. economy as a whole. Third, as the Mexican peso continues its fall against the U.S. dollar, people on both sides of the border grow wary of another unplanned devaluation. Lastly, the volatility of the peso and the North American Free Trade Agreement (NAFTA) make the forecast of the future spot rates of the Mexican peso and the U.S. dollar even more critical which is the purpose of this study.

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Global Finance Journal, 8(2): 211-220
ISSN: 1044-0283

II. LITERATURE REVIEW

There is an extensive empirical literature in finance and economics on testing the efficiency of various foreign exchange markets, determining exchange rates, and applying appropriate models to forecast exchange rates. However, the results of the previous studies—including Kaminsky and Peruga (1991), Isard (1988), Somanath (1986), and Rhim and Khayum (1994) indicate that additional research is needed on the predictive power of exchange rate forecasting models. Rhim and Khayum (1994) asserted that two commonly used techniques or models are (1) market-based forecasting, which emphasizes the process of developing forecasts from market indicators such as spot rates and forward rates; and (2) fundamental forecasting, which is based on underlying relations between variables and exchange rates. However, as an alternative model for improving the predictive power of foreign exchange rate forecasts, Fang and Kwong (1991/92), Kwok and Lubecke (1990), and Wolff (1988) suggested composite forecasting. Additionally, Gupta (1981) and Noorbakhsh and Shahrokhi (1993) in an empirical study of 12 currencies, using causality relationship method advanced by Granger (1969) found that, despite their thin trading and illegality, black markets rates were relatively efficient predictors of the official exchange rates.

Meese and Rogoff (1983) studied the forecasting power of several structural exchange rate models and found that structural models failed to improve upon simple random-walk forecasting models. Wolff (1988) compared the performances of 'news' models of exchange rate forecasting with random-walk models. He observed that for several exchange rates the news model was better than random-walk model. However, for a majority of the exchange rates studied the results obtained by the news model did not compare favorably with those obtained from the naive random-walk forecasting model. Krasker (1980) examined the 'Peso Problem' in testing the efficiency of the forward exchange markets. The results showed that Type I error was prevalent with forward rates and contributed to bias in the survey samples than forward rates as predictors of future spot rates. Canova and Murrinan (1992) examined whether changes in the perceived risk of engaging in a forward contract can account for fluctuations in observed profits. They found forward rates to be biased predictors of future spot rates and concluded that comparing risk to expected rate of return may lead to misunderstanding the volatility by associating the volatility with the assumed risk when the investment was made.

Chiesari (1989) compared and contrasted the effect that a "dirty float" and a 'pure float' would have on the Mexican peso. The "dirty float" was defined as allowing the peso to fluctuate against the U.S. dollar within a desired range. The government would either support the peso (at the bottom range) or deflate the peso (at the top range) using market mechanisms such as buying/selling pesos with/for U.S. dollars. While the "dirty float" supported short-term stability and increased preferred commerce, it also mislead the government and people by not addressing the real problem. The 'pure float' was superior because the government was forced to adjust to a constantly changing environment.

Krugman and Rotemberg (1990) studied the causes and probabilities of unsuccessfully maintaining a targeted currency zone. Their model used unsterilized intervention to maintain the zone when reserves are low. The speculative attack on the target zone is countered with the belief that the government is going to support the zone in the short-run. However, the knowledge that reserves are insufficient to support the zone under stress leads to a stronger attack and the downfall of the zone. A country with large reserves will deplete its reserves over time when defending a target zone. The reasoning is that when a currency threatens to go below the zone, reserves are expended to support the currency. To keep the currency below the upper limit, the home currency is bought back at inflated prices, resulting in the loss of control.

Longworth (1981) examined the efficiency of the Canadian-U.S. Exchange Market for the current float. The semi-strong form tests, which admit the lagged spot rate as predictor, were considered in addition to the standard weak-form test. He found that for almost every year of the study (July 1970 to December 1978) the current spot rate provided a better forecast of the future spot rate than did the current forward rate.

The main objectives of this study are to (1) determine which of the four models (ARIMA, Forward Rate, Random-Walk, and Spot) could accurately forecast the peso/dollar spot rates for the future, and (2) learn if peso investors could hedge investments against devaluations of the peso during 1983 to 1992 period.

III. SAMPLE DATA AND FORECASTING MODELS

The daily spot exchange rates for the Mexican peso and the U.S. dollar for one-year periods from January 1, 1982, to December 31, 1989, and for six-month periods from January 1, 1990, to December 31, 1992, were used to forecast peso/dollar future spot rates by applying four different forecasting techniques. Table 1 shows

Table 1
Time and Number of Observations of the Peso/Dollar Exchange Rate

Set	*Start*	*Finish*	*Number of Observations*
1	January 1, 1982	December 31, 1982	253
2	January 1, 1983	December 31, 1983	254
3	January 1, 1984	December 31, 1984	254
4	January 1, 1985	December 31, 1985	254
5	January 1, 1986	December 31, 1986	251
6	January 1, 1987	December 31, 1987	253
7	January 1, 1988	December 31, 1988	254
8	January 1, 1989	December 31, 1989	252
9a	January 1, 1990	June 30, 1990	126
9b	July 1, 1990	December 31, 1990	127
10a	January 1, 1991	June 30, 1991	125
10b	July 1, 1991	December 31, 1991	128

the time and the number of observations for data provided by the Multinational Computer Models, Inc.

The four models used in this study are the ARIMA, Forward Rate model, Spot-Rate or Regression model, and the Naive or Random-Walk method which are briefly explained below.

1. ARIMA is an acronym for AutoRegressive Integrated Moving-Average models, usually denoted by the notation ARIMA (p,d,q), where:

   p is the degree of the autoregressive part
   d is the degree of the differencing
   q is the degree of the moving-average process

   The ARIMA procedure models the behavior of a variable that forms an equally-spaced time series with no missing values. There are various types of ARIMA models, each one corresponding to the pattern and behavior of the univariate data. The peso data did not present any degree of seasonality, thus allowing simplification to only degrees of p, d and q. Additionally, SPSS software permits calculation of ARIMA variables utilizing individual degrees of p, d and q. The mathematical model is written:

$$W_t = \mu + \Sigma\Psi_i(\beta)X_{i,t} + [\theta(\beta)/\varphi(\beta)]a_t \tag{1}$$

Where:

W_t is the original data or a difference of the original data
t indexes time
(β) is the backshift operator; that is, $(\beta)X_t = X_{t-1}$
$\varphi(\beta)$ is the autoregressie operator
μ is the constant term
$\Theta(\beta)$ is the moving-average operator
a_t is the independent disturbance, also called the random error
$X_{i,t}$ is the ith input time series or a difference of the ith input time series at time t
$\Psi_i(\beta)$ is the transfer function weights for the ith input series (modeled as a ratio of polynomials). $\Psi_i(\beta)$ is equal to $\omega_i(\beta)/\delta_i(\beta)$, where $\omega_i(\beta)$ and $\delta_i(\beta)$ are polynomials in β.

2. The forward rate model regresses the last period's value of forward rate against the current period's value of spot rate over sample period. Equation (2) defines the forward rate model:

$$S_t = a_o + a_1F_{t-1} + e_t \tag{2}$$

Where S_t is log of the spot exchange rate at time t, F_{t-1} is the log of the forward exchange rate at time $(t - 1)$, and e_t is a random disturbance term.

This model hinges on the idea that the forward rate should move toward the market's general expectation of the future spot rate through the arbitrage process between traders for both spot deals and forward contracts. In this context, forward exchange rates reflect the market's expectation of the spot rate at the end of the forward horizon.

3. The Spot Rate or Regression model regresses the last period's value of spot rate against the current period spot rate over the sample period. This model contends that the best forecast of the future spot rate is the current spot rate, since the current spot rate represents the market's expectation of the spot rate in the near future. The model is expressed by Equation (3).

$$S_t = \beta_o + \beta_1 S_{t-1} + \varepsilon_t \tag{3}$$

Where S_t is the log of the spot exchange rate at time t, S_{t-1} is the log of the spot exchange rate at time $(t-1) < \beta_1$ is the slope of the regression, and ε_t is a random disturbance term.

4. The Random-Walk or Naive model is the no-change forecasting model in which a known exchange rate at time "t" is used to forecast the future exchange rate. In the context of efficient foreign exchange market, the exchange rate follows a random walk because it responds to new information received by the market which, by definition, is not predictable.

The exchange rate forecasts for twelve data periods are performed individually for each period. Forecasting accuracy of each technique is measured by four summary statistics that are standard throughout the modeling community: the Mean Absolute Error (MAE), the Mean Square Error (MSE), the Root Mean Square Error (RMSE), and the Expiration Day Error of the forward rate (EDE). These statistics are computed using the following equations:

$$\text{MAE} = \sum_{j=0}^{N-1} |A(K) - F(K)|/N$$

$$\text{MSE} = \sum_{j=0}^{N-1} [A(K) - F(K)]^2/N$$

$$RMSE = \left[\sum_{j=0}^{N-1} [A(K) - F(K)]^2/N\right]^{0.5}$$

$$\text{EDE} = [E(K) - F(K)]$$

Where $K=1, 3, 6, 12$ denotes the forecast steps, N is the total number of forecasts in the projection for which the actual value of the exchange rate,

E_t is known, and F is the forecast value for 1, 3, 6, and 12-month forward rates.

The first part (forecast) of the data series is used to estimate the second part (predictions). MAE, MSE, and RMSE calculations are based on the estimates from the prediction errors in the second part of the data series. The MAE measures the absolute sum error. The MSE and RMSE equations penalize deviations more heavily than does the MAE calculation. Two naive models are calculated, one using the no-change forecasting model and the other using a constant percentage increase formula. The use of two naive models is beneficial when determining the performance of the ARIMA models because, at times, peso exchange rates move linearly, randomly, or experience no change.

The ARIMA 1, 3, 6, and 12-month forward rates are estimated using the last day of the series as the base. The 1, 3, 6, and 12-month forward rates are based on 21, 63, 126, and 2 times the number of days in the estimation period, respectively.

ARIMA models are chosen according to differencing, t-value(s) of the coefficient(s), t-value(s) of the residual autocorrelations, Chi-squared test of the residual autocorrelations, Durbin-Watson statistic, and the F-statistic.

IV. ANALYSIS AND RESULTS

First, the d term in ARIMA (p,d,q) is estimated to create a stationary mean. When data are differenced to stabilize the mean, as with set 1 (difference = 1), the parameters are estimated without a constant term. Differenced observations typically have a mean very close to zero. Therefore, there is no deterministic trend element in the estimated parameter(s).

Second, other than constants, values of estimated parameters must be less than 1.0 and statistically significant at an absolute t-value of 2.0 or greater. This ensures that the standard error is minimal when compared with the estimated parameter and satisfies the requirement that parameter(s) be significantly different than zero.

Third, while significant parameter t-values are desired, both insignificant residual autocorrelation t-values and Chi-squared values are preferred. Insignificant t-values and Chi-squared values provide evidence that the error terms of consecutive estimations are independent.

Table 2 summarizes the result of the forecast for 1983, using data of 1982 and applying four different methods. It shows the type of ARIMA model, the t-statistic for each parameter, and the Durbin-Watson statistic. The AR1 and MA1 represent 1-day moving averages of error and the previous day's predicted spot rate, respectively. The t-statistic for each parameter is significant (greater/less than +/-2.0) at -14.06 and 49.00, respectively. When the t-statistics are significant, the standard error of the estimate is minimized. The Durbin-Watson test is utilized to ensure that the model does not have significant degrees of serial correlation, or underestimated variances, which cause the parameters to be greater than what should exist. The

Durbin-Watson statistic should be close to 2.00 to minimize serial correlation. The Durbin-Watson statistic ranges from 0 to 4. A value less than 2 indicates positive autocorrelation; values greater than 2 indicate negative autocorrelation. The model passed this test with 2.00. When the Durbin-Watson indicate autocorrelation, all possible combinations of AR, differences, and MA's were tested, from level 1 to level 5. After exhausting all combinations of AR, differences, and MA's, the model which produced the most significant t-statistic(s) and insignificant Durbin-Watson test statistic was accepted as the ARIMA model for that particular estimation period.

The ARIMA, slope (continuation of estimation period's slope into the prediction period), naive (last spot rate in estimation period projected into the prediction period), and forward rate (the published forward rate) models are compared using the MAE, MSE, RMSE, and EDE. The model which minimizes the prediction error in each of the MAE, MSE, RMSE, and EDE categories is denoted by an asterisk.

As Table 2 shows, in the case of the 1982 forecast of 1983, the ARIMA model outperformed all other models in the MAE, MSE, RMSE, and EDE categories for

Table 2
The Result of the 1982 Forecast for 1983

	OBS. 253	*ARIMA Model (T-Statistic), AR1(-14.06), MA1(49.00), Durbin-Watson Stat = 2.00221*		
1 Month Forecasts	ARIMA	Regression	Naive	Forward
MAE	0.000013375*	0.0000188818	0.0000183747	.0004545
MSE	0.000000002*	0.0000000051	0.0000000048	.0000003
RMSE	0.000052936*	0.0000714335	0.0000695132	.0005776
EDE	-.000004100*	.0000425000	.0000419000	.0008217
3 Month Forecasts	ARIMA	Regression	Naive	Forward
MAE	0.000053837	0.0000512810*	0.0000527287	.00071250
MSE	0.000000015	0.0000000138*	0.0000000144	.00000143
RMSE	0.000123989	0.0001175782*	0.0001202032	.00119495
EDE	.000243290*	.0003175100	0.0067566700	.00109849
6 Month Forecasts	ARIMA	Regression	Naive	Forward
MAE	0.000088258	0.0001087520	0.0001005174	-.0000205*
MSE	0.000000021*	0.0000000292	0.0000000256	.0000118
RMSE	0.000146281*	0.0001709843	0.0001599234	.0034347
EDE	-.000043100	.0000511000	0.0000208000*	.0026830
12 Month Forecasts	ARIMA	Regression	Naive	Forward
MAE	0.000198328*	0.0002175195	0.0002077668	-.00607148
MSE	0.000000054*	0.0000000586	0.0000000551	.00008723
RMSE	0.000232358*	0.0002420513	0.0002347186	.00933978
EDE	-.000580960	-.0004583800*	-.0005168900	.00288872

Note: *Denotes the best outcome between models.

the 1-month forecasting period. The ARIMA model was also optimal for the 3-month EDE, 6-month MSE, 6-month RMSE, 12-month MAE, 12-month MSE, and 12-month RMSE. The slope or regression model was optimal for the 3-month MAE, 3-month MSE, 3-month RMSE, and 12-month EDE. The naive model was optimal for the 6-month EDE. The forward rate was optimal for the 6-month MAE.

Table 3 summarizes the results of the analysis which were summarized in eleven tables, similar to Table 2 prepared one for each year. Table 3 indicates that the ARIMA model out-performed the regression, naive, and forward models in predicting future spot rates. Overall, the ARIMA model surpassed the naive model by only one more prediction. The ARIMA model outperformed the naive model by 7 more accurate predictions in forecasting 1-month future peso/dollar spot rates, and for 3-month predictions, ARIMA outperformed both the native and the regression models by 4 more accurate predictions. For the 6-month forecast, the naive model outperformed the other 3, and in forecasting the 12-month future peso/dollar exchange rates ARIMA outperformed all three models. After the ARIMA model, the naive and regression models performed equally well. Using the expiration day error accuracy measure, the future spot rates were more accurately portrayed by the naive model (14 occurrences)

Table 3
The Numbers of Best Performances For Each Model

Period	*Accuracy Measured by*	*ARIMA Model*	*Forward Rate Model*	*Spot Rate Model*	*Naive Model*
One-Month	MAE	5	1	2	4
	MSE	6		2	4
	RMSE	6		2	4
	EDE	5	1	3	3
	SUBTOTAL	22	2	9	15
Three-Month	MAE	5		4	3
	MSE	5		4	4
	RMSE	5		4	4
	EDE	3	3	2	3
	SUBTOTAL	18		14	14
Six-Month	MAE	2		4	5
	MSE	3		4	5
	RMSE	3		4	5
	EDE	1	3	1	6
	SUBTOTAL	9		13	21
Twelve-Month	MAE	4		3	3
	MSE	4		3	3
	RMSE	4		3	3
	EDE	1	4	2	2
	SUBTOTAL	13		11	11
Grand Total		62	12	47	61

V. CONCLUSION

The main objective of this study was to determine if the peso could be modeled with accuracy, as determined by MAD, MSE, RMSE, and expiration day error. Using the summarizing tables as guides, and excluding the RMSE totals because of their redundancy with the MSE, the findings of this study indicate that, based on the lowest number of errors, the ARIMA model outperformed the Forward Rate model, the Spot Rate or Regression model, and the Naive or Random-Walk method in predicting future spot rates.

Moreover, there is a pattern as to which model performs well during any given 1-month, 3-month, 6-month or year-long period. For instance, the ARIMA shows superior prediction capacity in 1983, 1989, 1990, and 1991a. The regression model performed well during years, of 1985, 1986, and 1987. The naive model outperformed the other models in 1984, 1988, 1989 (tie with ARIMA), and 1992a. Finally, the forward rate model was the optimal predictor in 1987 (tie with regression).

Looking at the pattern of each of the successive years, one would think that the 6- and 12-month forward rates are predictable. The most obvious method is to choose the best performing model from the 1- and 3-month forward rates. Assuming this is the case, then those people desiring to hedge and speculate would have been more accurate in 7 out of 13 periods according to expiration error columns 6-month and 12-month. By no means is this statistically sound.

Investors wishing to hedge are interested in the expiration day error, not the MAD, MSA, or RMSE. This is the day that the forward contracts expire. For example, if investors wish to hedge peso investments for December 1983, they would choose the ARIMA model because of its superior expiration day error minimization during the 1- and 6-month forecasts (the choice of models is based on the discussion in the previous paragraphs). The investors' decision to buy or sell pesos forward depends on the estimated value of the peso from the model. If the estimated peso is lower/ higher than the forward rate, investors will buy/sell pesos forward.

Excluding transaction costs, investors who buy pesos forward one year would profit as follows:

1/1/83 Using ARIMA model, 1-year peso spot rate is estimated to be 100.2058605 peso to the dollar.
1/1/83 Spot rate is 30.6 pesos to the dollar (data provided by Multinational Computer Models, Inc.)
1/1/83 Investors convert pesos to dollars at 30.6 pesos to the dollar.
1/1/83 Buy pesos forward at 153.615 (data provided by Multinational Computer Models, Inc.) pesos to the dollar for one year.
12/31/83 Actual spot rate is 106.40 (provided by Multinational Computer Models, Inc.) pesos to the dollar.
12/31/83 Investors make a profit of 153.615—106.4 = 47.215 pesos to the dollar.

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