RANDOM WALK OR ARIMA? EXPLORING THE POWER OF PREDICTABILITY OF RUPEE-DOLLAR EXCHANGE RATE

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ABSTRACT

This paper examines the randomness and predictability of the rupee-dollar exchange rate. We developed a working hypothesis to compare the out-of-sample forecasting abilities of the ARIMA model to those of a pure random walk (RW). The results indicate that the rupee-dollar exchange rate not only exhibits a trend component but also a statistically significant one. Hypothesis testing reveals that the ARIMA model outperforms the pure RW model as a predictor. The error measures, using RMSE and MAE, demonstrate that the ARIMA model possesses more than twice the predictive power compared to the pure random walk. Therefore, it can be concluded that the rupee-dollar exchange rate is anything but a random walk.

Keywords: RWH, RMSE, MAE, Diebold-Mariano test, ARIMA

I. INTRODUCTION

The study of financial markets has long been a focal point in economic literature, driven by both intellectual curiosity and the potential for financial gain. One of the fundamental ideas in this field is that asset markets are highly efficient, meaning that current prices fully reflect all available information, making it impossible to consistently achieve excess profits using existing knowledge. This concept was formally introduced by Fama (1965) as the *Efficient Market Hypothesis (EMH)*.

While the EMH does not strictly require asset price changes to be independent over time, a weaker version—suggesting that current prices incorporate all past information—gained widespread acceptance in the 1970s. This led to the development of the *Random Walk Hypothesis (RWH)*, which implies that if only historical prices are considered, future prices remain unpredictable.

Despite its popularity, the RWH has faced criticism from both theoretical and empirical perspectives. Theoretically, researchers (Mark, 1985; Sims, 1984) have demonstrated that significant nonlinearities in asset price movements are consistent with general-equilibrium asset pricing models. Empirically, numerous studies have challenged the RWH by highlighting statistical irregularities. As early as the 1960s, Mandelbrot (1963) has observed non-normality in asset price distributions—characterized by leptokurtosis, skewness, and fat tails. Subsequent research (Turner & Weigel, 1990) has confirmed these findings, solidifying them as a stylized fact in financial economics. Additionally, extensive evidence of nonlinear dependencies has been reported, particularly in exchange rate movements (Hsieh, 1989).

However, caution is needed when interpreting existing tests for nonlinearities and chaotic behavior. Barnett et al. (1994) have highlighted significant methodological loopholes, noting that the reliability of such tests remains debated due to their lack of robustness, varying statistical power, and differences in null hypotheses.

These critiques have fuelled the search for forecasting models that can outperform the RWH in out-of-sample predictions. Early attempts, however, yielded disappointing results. As late as 1990, Diebold and Nason (1990) have acknowledged that while strong statistical evidence exists against the RWH, improving upon its predictability, particularly in comparison to linear models, remained an open challenge.

Meese and Rogoff (1983a, 1983b) brought a seismic shift in the literature of the economic modelling of nominal exchange. The study laid down numerous criteria for being optimistic about any model. Foremost was to outperform the pure Random Walk (RW) in out-of-sample. Since then, it has been widely accepted that pure RW is the best predictive model for exchange rate. However, the finding of Meese and Rogoff (1983a, 1983b) does not validate the EMH for nominal exchange rates (Rossi, 2013).

Recently, the quest to "beat the RWH" has become a central objective in financial data analysis. Nevertheless, the debate continues with no definitive resolution. The performance of multivariate (economic model) exchange rates in surpassing the RW has been dismal. Some scholars have tested this formidable univariate using other univariate models. A notable study includes Diebold and Nason (1990), Rapach and Wohar (2006), Lisi and Medio (1997), and West et al. (1993). However, the competing model was nonlinear and complicated in nature.

Thus, we tried pitting another univariate linear model against the most successful model (RW). We have used the ARIMA model (Geurts, 1977) as a competing model. This facilitates three objectives. Firstly, it helps in exploring the predictability of the rupee-dollar exchange rate. Secondly, address the randomness of the rupee-dollar exchange rate. Lastly, the research presented the equally straightforward forecasting method as RW, which enhances the forecasting of exchange rates when compared to more complicated methods.

Keeping our objective in our mind, we avoided using any statistical test; instead, we have developed a working hypothesis where we have conducted hypothesis testing of out-of-sample forecasting of competing models. The result showed the ARIMA model outperformed by a commendable margin.

The structure of the paper is outlined as follows: Section II presents a literature survey. Section III delves into the methodology and working hypothesis adopted for the study. Section IV explores the characteristics and source of the data, while Section V presents the empirical results. Section VI provides the concluding remarks for the paper. Section VII highlights practical implications of findings. Finally, Section VIII shed light on the future path of study.

II. REVIEW OF LITERATURE

Since the study focuses on univariate analysis encompassing the predictability and randomness of rupee-dollar exchange, we avoided discussing studies that featured highly structured data, such as Dua and Ranjan (2012), Engel (1994), Schinasi and Swamy (1989), Wolff (1987), and Engel and Hamilton (1990). We focused on studying the highlighted significance of pure RW in the nominal exchange rate.

The seminal paper of Meese and Rogoff (1983a &1983b), popularly known as the Meese and Rogoff Puzzle, altered the yardstick of economic modeling of the nominal exchange rate. Since then, it has been the undeniable fact that the economic model cannot out predict the random walk (Moosa & Burns, 2013). The results of subsequent studies supported the puzzle (Bacchetta et al., 2006). The paper's findings suggest that no perceived economic model could outperform the random walk. However, the striking feature of the paper was that Meese and Rogoff suggested that the out-of-sample fit should be given preference over the in-sample fit while being optimistic about any economic models. Tashman (2000) supported Meese and Rogoff's viewpoint that the prowess of an economic model should be judged based on an out-of-sample fit.

Although many models performed well regarding in-sample forecasting, they fail miserably in out-of-sample forecasting (Sarno & Taylor, 2002). The continuous failure to overturn the Meese and Rogoff result leads to criticism of the procedure. Engel and West (2004) argue that beating a pure RW should not be the criterion for being optimistic about the economic model, as an exchange rate itself is a pure RW. Engel et al. (2007) asserted a similar opinion that beating the pure RW model is very harsh on the economic modeling of exchange rates. The pure RW forecast for a particular point in time is the previous period's rate, which means that the forecasting error is the period-to-period change. Any model will struggle to beat the pure RW if the exchange rate is stable for small errors. If, on the other hand, the rate is volatile, the RMSE of the pure RW will increase, but so will the RMSE of the model, as it is more difficult for any model to forecast a volatile exchange rate than a less volatile one. It will be intriguing to find out, by conducting Monte Carlo simulations, if by increasing volatility, the RMSE of the model rises faster than the RMSE of the pure RW. If this is the case, then the failure of exchange rate models to outperform the random walk in terms of the RMSE becomes rather intuitive.

Another criticism of Meese and Rogoff's procedure was the use of RMSE as a forecasting evaluation that focuses on the magnitude of error, however, scholars such as West et al. (1993), Abhyankar et al. (2005), Christoffersen and Diebold (1998), Leitch and Tanner (1991), Cumby and Modest (1987), Cheung et al. (2005), and Cheung and Chinn (1998) emphasised that evaluation should be based of direction accuracy which is more appropriate than RMSE. They argued that the direction accuracy is more crucial than the magnitude of the error, as it enhances the profit-making ability of traders based on forecasting and should be the ultimate test for judgment of any model.

III. RESEARCH METHODOLOGY

The objective of study inspired us to adopt the methodology employed by Lisi and Medio (1997). The methodology is unique as used working hypothesis to address the randomness of nominal exchange. Following, the hypotheses were formulated.

HYPOTHESES

H_{01}: No difference in forecasting of Pure Random Walk and ARIMA

H_{02}: Forecasting of Model 1 (ARIMA) is not better than forecasting of Model 2 (Random Walk).

H_{03}: Forecasting of Model 2 (Random Walk) is not better than forecasting of Model 1 (ARIMA)

The mechanism behind such a working hypothesis is that a random walk should be best predicted by random walk estimation rather than any other model. In our case we have ARIMA model which linear and simpler model compare to Singular Spectral Analysis (SSA) used by Lisi and Medio. The rejection of H_{02}, justified that the lagged value does influence Y_t (exchange rate). Hence, cancelling the necessary condition that the series Y_t should not have any stochastic or deterministic trend to be called a pure RW. We have compared the out-of-sample forecasting using RMSE (Root Mean Square Error) and MAE (Mean Absolute Error).

RMSE,

$$\text{RMSE} = \sqrt{\frac{\sum_{j=1}^{N}(x_j - x_F)^2}{N}}$$

MAE,

$$\text{MAE} = \frac{\sum_{j=1}^{N}|x_j - x_F|}{N}$$

Lastly, evaluating the working hypothesis using the Diebold-Mariano test (HLN adjusted) developed by Diebold and Mariano (1995). Diebold-Mariano test is two tailed which perfectly suit the dynamic of our working hypothesis which itself two tailed in nature.

$$DM = \frac{D}{\sqrt{\frac{\varphi_0 + 2\sum_{K=1}^{M-1}\varphi_k}{T}}}$$

where:

D is the mean loss differential.

φ_0 is the autocovariance of D at lag 0

φ_k is the autocovariance of D at lag K

T is the number of observations.

M is the truncation lag, often chosen based on an information criterion.

IV. DATA

We have collected data on the Rupee-Dollar exchange from the official site of RBI (Reserve Bank of India). The range is from March 1993 to January 2023; hence, it encompasses the starting point of the floating regime. We have divided the data into 299 months for parameter estimation and 72 months for out-of-sample forecasting. A further 72-month forecasting horizon was divided into 12-month, 48-month, and 72-month. This approach gives us a significant advantage in short-term and long-term forecasting.

V. EMPIRICAL ANALYSIS

The result shows that not only the Rupee-Dollar exchange exhibits a trend component but also a statistically significant one. This is enough to conclude that the exchange rate is not a pure random walk; however, we have extended our empirical analysis to compare out-of-sample forecasting, on which our hypothesis was based.

The selection of the ARIMA model and estimation are presented in TABLE 1 and TABLE 2, respectively. The estimation of the pure random walk is presented in TABLE 3.

ARIMA ESTIMATION

We estimated the ARIMA (p, I, q) model for the EX-series and found it to be non-stationary, following an I(1) process, as expected. A trial-and-error approach was employed to compare the log-transformed series with the original series. It was determined that the first difference of the log-transformed series provided better forecasting results than the first difference of the original series. Consequently, we applied the Box-Jenkins methodology (Geurts et al., 1977) to the log series, resulting in the estimation of 25 models. The Akaike Information Criterion (AIC), as proposed by Akaike (1974), was utilized to select the best model from these 25 estimates. The results showed that the ARIMA model using the first difference operator, with four lags for both the autoregressive and moving average parts, was the best option because it had the lowest AIC value. The AIC results for each model are presented in TABLE 1.

TABLE 1: ARIMA MODEL SELECTION BASED ON AIC

Model	LogL	AIC	BIC	HQ
(4,1,4)	770.7307	-5.10558*	-4.98151	-5.05591
(2,1,2)	765.7783	-5.09918	-5.02475	-5.06939
(3,1,2)	765.9227	-5.09344	-5.0066	-5.05868
(3,1,3)	766.0168	-5.08736	-4.98811	-5.04763
(2,1,3)	763.8464	-5.07951	-4.99266	-5.04474
(2,1,4)	764.8257	-5.07937	-4.98012	-5.03964
(4,1,2)	764.7848	-5.07909	-4.97984	-5.03936
(4,1,3)	764.9619	-5.07357	-4.96191	-5.02888
(3,1,4)	764.7637	-5.07224	-4.96058	-5.02754
(4,1,0)	761.5446	-5.07077	-4.99633	-5.04097
(1,1,1)	759.1517	-5.06813	-5.01851	-5.04827

(4,1,1)	762.0612	-5.06753	-4.98068	-5.03276
(0,1,4)	760.5652	-5.0642	-4.98976	-5.0344
(0,1,3)	759.3791	-5.06295	-5.00092	-5.03812
(2,1,1)	759.3516	-5.06276	-5.00073	-5.03793
(3,1,1)	760.3349	-5.06265	-4.98821	-5.03285
(1,1,2)	759.3001	-5.06242	-5.00039	-5.03759
(0,1,2)	758.2004	-5.06175	-5.01212	-5.04188
(0,1,1)	756.8409	-5.05934	-5.02212	-5.04444
(1,1,3)	759.7098	-5.05846	-4.98402	-5.02866
(1,1,4)	760.566	-5.05749	-4.97065	-5.02273
(1,1,0)	756.5238	-5.05721	-5.01999	-5.04231
(3,1,0)	758.4713	-5.05685	-4.99482	-5.03202
(2,1,0)	757.2347	-5.05527	-5.00564	-5.0354
(0,1,0)	754.7455	-5.05198	-5.02717	-5.04205

Source: Authors

The R-squared and adjusted R-squared values for the ARIMA model were 0.105 and 0.077, respectively, with an F statistic of 3.77, indicating statistical significance at a 1% confidence level. The Durbin-Watson statistic for the model was 2.02, falling within the limits of 1.592 and 1.757, suggesting that the model does not exhibit autocorrelation.

The constant coefficient was 0.002459, with a t-value of 1.98, indicating statistical significance at a 5% confidence level. The AR(1), AR(2), AR(3), and AR(4) coefficients were -0.97, -1.03, -0.98, and -0.76, respectively, with corresponding t-values of -12.13, -15.62, -14, and -10.26, confirming their statistical significance. The MA(1), MA(2), MA(3), and MA(4) coefficients were 1.15, 1.12, 1.15, and 0.83, with t-values of 14.51, 18.98, 15.69, and 12.46, respectively, also indicating statistical significance. The coefficient of SIGMASQ (Sigma squared) was 88,696,336, with a t-value of 15.8, demonstrating its statistical significance in the established model. This is further illustrated in TABLE 2.

TABLE 2: ESTIMATION OF ARIMA

Dependent Variable: DLOG(PRICE)				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
Constant	0.002459	0.0012	1.98	0.0491
AR(1)	-0.97443	0.0803	-12.13	0.0000
AR(2)	-1.03643	0.0664	-15.62	0.0000

AR(3)	-0.98457	0.0704	-14.00	0.0000
AR(4)	-0.76906	0.0750	-10.26	0.0000
MA(1)	1.152476	0.0795 .	14.51	0.0000
MA(2)	1.121808	0.0591	18.98	0.0000
MA(3)	1.159706	0.0739	15.69	0.0000
MA(4)	0.83171	0.0667	12.46	0.0000
SIGMASQ	0.000331	0.0000	17.29	0.0000
R-squared	0.10556	Adjusted R-squared		0.077609
F-statistic	3.776572	Prob(F-statistic)		0.000162
Durbin-Watson stat	2.022187	Akaike info criterion		-5.105575
Inverted AR Roots	.25+.94i	.25-.94i	-.73-.53i	-.73+.53i
Inverted MA Roots	.22-.96i	.22+.96i	-.80+.47i	-.80-.47i

Source: Authors

PURE RANDOM WALK ESTIMATION

The EX-series is identified as an I(1) process, as previously discussed, allowing for a Pure Random Walk estimation without hesitation, as this is a necessary condition. The coefficient for lag 1 is 1.002177, indicating a near-perfect presence of a unit root at the 1% significance level. The R-squared value is 0.99, which aligns with expectations for a random walk model. Additionally, the Durbin-Watson statistic is satisfactory at 1.83, exceeding the upper limit of 1.79, suggesting no autocorrelation, which is consistent with a series that operates under a random walk.

TABLE 3: ESTIMATION OF PURE RANDOM WALK

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EX (-1)	1.002177	0.001163	862.013	0.00000
R-squared	0.99085	Adjusted R-squared		0.99085
F-statistic	862.013	Prob(F-statistic)		0.00000
Durbin-Watson stat	1.833237	Akaike info criterion		2.767236

Source: Authors

FORECASTING EVALUATION

The empirical analysis of forecasting evaluation of two models, which are further divided into hypothesis test (along with direction) and magnitude of error, i.e., percentage improvement in accuracy indicates that the Diebold-Mariana test must be significant for all forecasting horizons. At absolute level ARIMA model showed improvement of 214% (RMSE) and 239% (MAE) for 12-month forecasting horizon. For 48-month forecasting horizon accuracy improve by 242% (RMSE) and 262 (MAE) which further improvement compare to 12-month forecasting horizon. The 72-month forecasting horizon showed improvement with par to 12-month horizon with 218% (RMSE) and 234% (MAE). Refer to TABLE 4.

The same was revealed through hypothesis testing (H_{01}), that the statistical difference in accuracy exist between the two models. Hence, H_{01} is rejected at 1% significance level all forecasting horizons (TABLE 5-7). The further investigation of the test reveals that H_{02} is rejected at 1% significance level all forecasting horizons, which was evident from previous section as ARIMA model was more accurate in forecasting EX as compare Random Walk. Thus, proving that the ARIMA model as a better predictor all forecasting horizons. The rejection of H_{01} and H_{02} means that H_{03} must be accepted since the Diebold-Mariano is two tail test and same is evident from TABLE 5-7.

TABLE 4: FORECASTING EVALUATION OF PURE RANDOM WALK AND ARIMA

12-Month Horizon			
Method	**ARIMA**	**Pure Random Walk**	**Accuracy**
RMSE	4.13	8.84	**214%**
MAE	3.64	8.61	**239%**
48-Month Horizon			
	ARIMA	**Pure Random Walk**	**Accuracy**
RMSE	3.75	9.08	**242%**
MAE	3.41	8.94	**262%**
72-Month Horizon			
	ARIMA	**Pure Random Walk**	**Accuracy**
RMSE	4.84	10.58	**218%**
MAE	4.39	10.29	**234%**

Source: Authors

TABLE 5: HYPOTHESIS TESTING FOR 12-MONTH FORECASTING HORIZON

Accuracy	Statistic	H_{01}	H_{02}	H_{03}
Abs Error	-150.21	0.000	0.000	1.000
Sq Error	-11.056	0.000	0.000	1.000

Source: Authors

TABLE 6: HYPOTHESIS TESTING FOR 48-MONTH FORECASTING HORIZON

Accuracy	Statistic	H_{01}	H_{02}	H_{03}
Abs Error	-84.729	0.000	0.000	1.000
Sq Error	-28.014	0.000	0.000	1.000

Source: Authors

TABLE 7: HYPOTHESIS TESTING FOR 72-MONTH FORECASTING HORIZON

Accuracy	Statistic	H_{01}	H_{02}	H_{03}
Abs Error	-72.463	0.000	0.000	1.000
Sq Error	-21.593	0.000	0.000	1.000

Source: Authors

VI. CONCLUSION

The study explores both the predictability and randomness of the rupee-dollar exchange rate. We developed and tested working hypotheses to observe whether ARIMA can outshine pure RW in out-of-sample forecasting. The Diebold-Mariano test was used to verify hypotheses.

The result exhibits that the ARIMA model is a better predictor of the rupee-dollar rate than the pure RW. The magnitude of the error measured by using RMSE and MAE shows that the ARIMA model has more than twice the predictive power compared to the pure RW. Thus, it would not be unwise to say that the rupee-dollar exchange rate does not follow a pure RW.

VII. PRACTICAL IMPLICATION

The use of pure RW as a forecasting tool is prevalent among brokers, banks, and concerned government authorities. The major reasons behind such widespread applicability are the accuracy and simplicity of the model though such a model has some complexity, preventing its widespread use. The non-linear model has performed better than pure RW on such occasions. Thus, such a study remains confined to literature only without any practical implications. However, the ARIMA model is not only a substitute for the accurate prediction of pure RW but also offers some amount of simplicity.

VIII. SCOPE

The results indicate that the rupee-dollar exchange rate shows a specific trend. Therefore, by incorporating a random walk (RW) with drift as an exponent of stochastic trends, we can expand the subsequent study. A comparative analysis of three competing models may offer further details about the predictability of the rupee-dollar exchange rate, which in turn, will offer a better insight into the models.

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