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EXCHANGE RATE FORECAST FUTILITY FOR THE TAKA

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Abstract

An autoregressive distributed lag (ARDL) version of an error correction model based on a balance of payments approach is used to forecast the nominal exchange rate for the Bangladeshi taka. Based on existing trade volumes and trade practices, the bilateral exchange rate of the taka with the dollar is analyzed. Annual frequency data for a four decade period from 1976 to 2015 are utilized for the study. Descriptive statistics, formal inferential tests, and directional accuracy tests are used to assess out-of-sample forecast accuracy. Results indicate that, in spite of good in-sample estimation diagnostics, the model forecasts do not fare well against random walk benchmarks.

Keywords: Bangladesh, Taka, Bilateral Exchange Rate Forecast Accuracy

JEL Classification: F31, O53

1. Introduction

Currency market values are difficult to predict. Simple random walk (RW) forecasts are often relatively effective in predicting future values of the exchange rate (Kilian and Taylor, 2003). However, error correction models can often be useful because this approach allows examination of long-run and short-run exchange rate dynamics.

This study models the bilateral exchange rate between the Bangladesh taka and the United States dollar using an autoregressive distributed lag (ARDL) approach. To date, relatively little research of this nature exists for the taka. That represents a curious gap in the international economics literature given the status of Bangladesh as the eighth most populous country in the world with the 31st largest economy in aggregate terms (IMF, 2018). This effort attempts to at least partially fill that breach in this branch of the discipline.

Forecasts are generated for this bilateral exchange rate and out-of-sample simulation performance is examined using various measures. Those measures include traditional descriptive accuracy statistics, formal inferential accuracy tests, and formal directional accuracy tests. In spite of relatively good in-sample ARDL model properties (Fullerton *et al.* 2017), the out-of-sample forecast performance of the model is not very strong. Subsequent sections of the study include a brief overview of prior research, methodology employed, and forecast accuracy assessments. A conclusion summarizes the results obtained.

2. Literature Review

Several previous studies examine exchange rate forecasts using error correction modelling strategies. Dynamic error correction frameworks sometimes produce exchange rate forecasts that are superior to those generated by following random walks (MacDonald and Taylor, 1993; Kim and Mo, 1995; Reinton and Ongena, 1999). Results do not, however, unanimously favor any type of formal econometric modelling strategies.

Exchange rate model out-of-sample forecasting performances are also affected by the evaluation methodologies employed (Moosa and Burns, 2013). Structural models frequently outperform random walks when forecast quality is measured in terms of economic value and directional accuracy (Moosa and Burns, 2014; Moosa and Vaz, 2015). Specification quirks, dynamic market changes, as well as erroneous explanatory variable forecast paths can still hamper the accuracy of currency model forecasts along those dimensions of appraisal, also (Neely and Sarno, 2002; Moosa and Vaz, 2016).

One recent study uses an ARDL error correction approach to model the taka/dollar exchange rate (Fullerton *et al.* 2017). Results indicate that a balance of payments framework works more reliably than a monetary model for analyzing variations in the taka/dollar bilateral relationship. This study employs the balance of payments model to generate out-of-sample forecasts of the taka/dollar exchange rate. For economies whose currencies can be affected by balance of payment inflows or outflows, the balance of payments approach provides a logical framework for analyzing currency market values. Fullerton *et al.* (2017) provide empirical evidence that supports the balance of payments approach (Dornbusch and Fischer, 1980) over a competing monetary balances model (Baillie and Selover, 1987) that has also proven useful in prior exchange rate forecasting studies. The simulation methodology is summarized next.

3. Methodology

A theoretical version of a Dornbusch and Fischer (1980) balance of payments model is shown in Equations (1) and (2).

$$s_t = a_0 + a_1(p - p^*)_t + a_2 (r - r^*)_t + a_3 IR_t + u_t \tag{1}$$

$$d(s_t) = b_0 + b_1 d(p - p^*)_t + b_2 d(r - r^*)_t + b_3 d(IR_t) + b_4 u_{t-1} + v_t \tag{2}$$

Equation (1) captures long-run equilibrium dynamics and shows the nominal taka/dollar exchange rate (s) as a function of national price level (p) differences, interest rate (r) differentials, international liquid reserves (IR), and a stochastic error term (u). The variables s, p, and IR are expressed in natural logarithms while r is expressed as a percentage. Asterisks denote variables corresponding to the United States while t is a time subscript. The remaining explanatory variables correspond to Bangladesh. Slope coefficients symbolize the marginal effects of the explanatory variables on the taka / dollar exchange rate.

The short-run behavior of the exchange rate with error correction is shown in Equation (2). In Equation (2), d is a difference operator and v is a white noise random disturbance term. Changes in the taka/dollar exchange rate can be affected by short-run and long-run forces. Long-run dynamics enter into Equation (2) via the lagged residuals, u_{t-1}, from Equation (1).

Details regarding the data and ARDL estimation results are discussed in Fullerton *et al.* (2017). Using the theoretical balance of payments specifications from above, Equation (3) results from solving for u_t and then substituting a one period lag of that expression into Equation (2). A forecast equation for the exchange rate in level, rather than first-differenced, form is then obtained by rearranging terms for simulation purposes.

$$s_t = \mu_0 + \mu_1 s_{t-1} + \mu_2 d(s_{t-1}) + \mu_3 d(p - p^*)_t + \mu_4 d(r - r^*)_t + \mu_5 d(IR_t) + \mu_6 d(IR_{t-1}) - \mu_7 (p - p^*)_{t-1} - \mu_8 (r - r^*)_{t-1} - \mu_9 IR_{t-1} + v_t \quad (3)$$

Using Equation (3), annual frequency exchange rate forecasts are produced for the years 2007 to 2015. The sample data used for estimation purposes begins in 1976 and, initially, runs through 2006. In order to provide an adequate number of observations for statistical analysis of forecast accuracy, an expanding re-estimation and simulation procedure is employed. A total of 21 forecast observations are generated using this procedure. Random walk and random walk with drift forecasts are used as comparative benchmarks. Historical data employed are from the International Monetary Fund (Fullerton *et al.* 2017).

Four types of evaluation metrics are used to examine predictive accuracy. Descriptive forecast evaluation statistics include Root Mean Squared Error (RMSE) and Theil U-statistics (Pindyck and Rubinfeld, 1998). Formal accuracy tests proposed by Diebold and Mariano (1995) and Ashley *et al.* (1980) are also employed. Both tests involve null hypotheses of mean squared error (MSE) equality of the RW forecast errors and the ARDL forecast errors. Finally, directional accuracy analysis is used to evaluate predictive accuracy. The Pesaran and Timmermann (1994) procedure tests the null hypothesis that actual and predicted directional changes are independently distributed. If the null hypothesis is rejected, the forecasts provide useful information on the direction of change (Granger and Pesaran, 2000).

4. Forecast Accuracy Analysis

Tables 1 through Table 4 examine out-of-sample prediction accuracy of the taka forecasts relative to the random walk benchmarks. The most accurate forecasts are shown in bold. Table 1 reports RMSE and Theil U-statistics. The Theil U-statistics indicate that the balance of payment ARDL model forecasts (denoted ARDL) are less accurate than those of the random walk (RW) and those of the random walk with drift (RWD). That is similar to what Fullerton and Lopez (2005) documents for the Mexican peso. Similar evidence has been documented for other currencies (Moosa and Burns, 2014). All three sets of taka forecasts analyzed in Table 1 are found to be unbiased.

The information provided in Table 1 is useful, but descriptive, only. Nonparametric Diebold-Mariano statistics shown in Table 2 indicate that the RW and RWD benchmarks provide significantly more accurate forecasts than the ARDL model. Those outcomes are similar to the results for high-income country exchange rate forecasts reported in Berkowitz and Giorgianni (2001).

Table 1. RMSE and Theil U-statistics

	ARDL	RW	RWD
RMSE	0.1794	**0.0479**	0.0637
U-statistic	0.0209	0.0056	**0.0074**
U-Mean (Bias)	0.0273	0.1340	**0.0077**
U-Variance (Variability)	0.2121	**0.0020**	0.2769
U-Covariance (Random)	0.7835	**0.8640**	0.7154
Number of forecast observations.	21	21	21

Notes: Optimal distribution for second moment proportions is $U^M = U^V = 0$, $U^C = 1$.

Table 2. Diebold-Mariano Non-Parametric Test Results

Test		DM statistic	Decision
Diebold Mariano	ARDL vs. RW	7.451**	**Reject (0.0000)**
	ARDL vs. RWD	6.351**	**Reject (0.0000)**

Notes: Null Hypothesis, $H_0: \mu(MSE(e_1) - MSE(e_2)) = 0$, where $MSE(e_1)$ is the mean squared error statistic for the ARDL forecast. **Significant at 1%.

The relative accuracy of competing forecasts can be further assessed through an error differential regression test (Ashley *et al.* 1980). The mean error values of the three sets of forecasts have different signs and that affects the interpretation of these results. The forecast error means are -0.012 for the ARDL model, -0.0175 for the RW, and 0.006 for the RWD. Conclusions regarding the relative accuracy of competing sets of forecasts also depend on the signs of the constant terms and slope parameters for each error differential equation. For the ARDL vs. RW comparison both estimated coefficients are positive, while those for the ARDL vs. RWD comparison are of opposite signs, with β_1 negative and β_2 positive.

Table 3. Error Differential Regression Test Results

Test		F-Stat	
Error differential regression	ARDL vs. RW	42.64 **	**Reject**
	ARDL vs. RWD	14.57**	**Reject**

Notes: Null Hypothesis, $H_0: MSE(e_1) = MSE(e_2)$, $MSE(e_1)$ is the mean squared error statistic for the ARDL forecast. **Significant at 1%.

Table 3 summarizes the error differential regression test results. For the ARDL vs RW comparison, the sign of β_1 indicates that the ARDL forecasts are superior (although the coefficient is statistically insignificant), while the sign of β_2 is consistent with RW superiority (this coefficient is statistically significant). Because the coefficient signs point to opposite conclusions regarding which set of forecasts is better, a one-tailed t-test is used to test the null hypothesis $\beta_2 \leq 0$ against the alternative hypothesis $\beta_2 > 0$ (Ashley *et al.* 1980). In the ARDL vs. RWD comparison, the signs of both regression coefficients indicate that the RWD projections are superior. Because both coefficient signs point to consistent conclusions regarding which set of forecasts is better, an F-statistic is calculated for the hypothesis $\beta_1 = \beta_2 = 0$. For both sets of regression equations, the ARDL predictions are found to be relatively less accurate than the random walk benchmarks. These results are similar to those documented in other exchange rate studies (Meese and Rogoff, 1983; Moosa and Vaz, 2016).

In addition to forecast accuracy, directional forecast evaluations are also completed for the ARDL forecasts. In Table 4, the computed Pesaran-Timmermann statistic is lower than the 5% critical value for a one-sided normal test and the null hypothesis cannot be rejected. That indicates that the ARDL taka forecasts fail to provide useful information on the direction of change for the bilateral exchange rate.

Table 4. Directional Accuracy Test for ARDL Forecasts

Statistics	Value	Conclusion
PT Statistics	- 0.6845	**Do not Reject**

Note: Null hypothesis, H_0: Actual and predicted directional changes are independently distributed. $\Sigma_{i=1}^{m} (p_{ii} - p_{i0}p_{0i}) = 0$; implies that ARDL forecasts do not predict exchange rate direction of change.

Overall, the ARDL balance of payments model falls short of the random walk benchmarks in out-of-sample forecasting performance. Moosa and Burns (2014) indicate that monetary models can outperform the random walk in out-of-sample simulations if forecasting power is measured by directional accuracy and profitability. Profitability is more closely related to directional accuracy than to the magnitude of the error term (Moosa and Vaz, 2015). However, Fullerton *et al.* (2017) provide evidence that the balance of payment approach works better for analyzing variations in the taka / dollar exchange rate than does the monetary approach.

While the forecasting performance of the ARDL model is not good, the diagnostic statistics in Table 1 indicate that the forecasts are unbiased. The model can potentially be used to simulate the effects of changes in key explanatory variables such as international reserves. A theft of funds from the central bank of Bangladesh in 2016 represents an example of an appropriate context for this type of application. By exploiting cyber-security weaknesses, hackers were able to steal $81 million from the Bangladeshi foreign reserves (Maurer *et al.* 2017). The ARDL balance of payments model could be used to simulate the short- and long-run repercussions of this incident on taka / dollar exchange rate dynamics. Simulations of this nature might be useful to policymakers in quantifying the impacts of such incidents on macroeconomic stability and in evaluating the costs and benefits of financial cyber-security precautions.

Of course, the modelling approach employed relies upon a very small ARDL modelling framework that consists of a system of two equations (Fullerton *et al.* 2017). An alternative strategy would be to develop a more fully articulated model involving more aspects of the Bangladesh national economy. Such efforts have been deployed with varying degrees of empirical success for other developing economies (Fullerton, 1993a, 1993b). That type of effort would likely yield additional insights with respect to macroeconomic conditions in Bangladesh, but whether better exchange rate forecast accuracy would be attained is unknown at this juncture.

6. Conclusion

The study examines the accuracy of out-of-sample taka / dollar exchange rate forecasts generated with an ARDL model developed from a balance of payments approach. Random walk and random walk with drift benchmarks are used to evaluate predictive accuracy. Descriptive statistic, non-parametric test, and error differential regression test evidence indicate that the ARDL forecasts are less accurate than those of the benchmarks. Furthermore, a directional forecast evaluation test implies that the ARDL forecast fails to provide useful information on the direction of change for the taka. Although the sample size is fairly small, these results indicate that it will be very difficult to forecast this bilateral exchange rate and close attention should be paid to recent history by business analysts, currency traders, and investors.

These results should be regarded as unique to the bilateral taka/dollar exchange rate. Similar difficulties have been documented with respect to out-of-sample forecast efforts for many other currencies. What is different about the taka, however, is that this currency has been in existence less than fifty years and historical data for it, and most other macroeconomic variables in Bangladesh, are in relatively short supply. Given that, it will be important to re-visit the topic of this study again as the economic history of Bangladesh becomes more extensive and more data become available. It will also be useful to eventually conduct similar efforts for the taka using higher frequency data than the annual information employed above.

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