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Error Correction Exchange Rate Modeling For Bangladesh

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Abstract

Several error correction models are estimated for analyzing the nominal exchange rate dynamics of Bangladesh between the taka and the United States dollar using annual data. The theoretical frameworks utilized include balance of payments and the monetary construct. The bilateral taka / dollar exchange rate model based on the balance of payments approach exhibits better econometric and statistical traits than the model based on the monetary construct. Out-of-sample simulation indicates, however, that the balance of payments ARDL model does not generate very accurate forecasts for this bilateral exchange rate.

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Chapter 1: Introduction

Currency market values are difficult to model (Uddin et al., 2013). Simple random walk forecasts are often relatively effective in predicting future values of the exchange rate (Kilian and Tylor, 2003). However, error correction models are often useful for analyzing nominal exchange rates, because this approach allows examination of long-run and short-run exchange rate dynamics.

The objective of this study is to analyze the behavior of the nominal taka / dollar exchange rate using annual data from 1976 to 2015. The taka is the national currency of Bangladesh. Since the United States dollar is commonly utilized to carry out international trade transactions of Bangladesh with rest of the world, the taka / dollar exchange rate is selected for the analysis. The research follows an error correction procedure similar to that employed by Fullerton and Lopez (2005) for the Mexican peso / United States dollar exchange rate. The analysis employs traditional balance of payments and monetary constructs (Dornbusch and Fischer 1980; Baillie and Selover 1987).

The study is organized as follows. The second section provides a brief review of the literature. Data and theoretical models undergirding the econometric analysis are introduced in section three. Section four discusses empirical estimation results. Out-of-sample simulation properties are evaluated in section five. The final section concludes and summarizes the study.

Chapter 2: Literature Review

Exchange rates are affected by many macroeconomic variables. Some of the major factors influencing exchange rate dynamics include national price levels, interest rates, real output levels, money supplies, and international trade balances (Isard, 1987; Hopper, 1997). Exchange rates, in turn, influence international prices of goods and services and, consequently, volumes of exports and imports (Makin, 2002).

The balance of payments is the international balance sheet of a nation that records all international transactions in goods, services, and assets during a specific period of time. Whenever the balance of payments registers a purchase of a foreign asset or a sale of a domestic commodity abroad, this implicitly indicates that there is a change in the demand for or in the supply of a foreign currency. The exchange rate is the value at which the supply and the demand for the foreign currency in terms of the local currency equilibrates. Makin (2009) notes that the exchange rate is based on relative movements in the supply and demand for currencies arising from external account transactions such as imports, exports, and foreign investment flows. Therefore, changes in balance of payments can cause fluctuations in the exchange rate between the domestic and foreign currencies.

Monetary factors also play significant roles in exchange rate behavior (Baillie and Selover, 1987). According to the monetary approach, the equilibrium exchange rate changes due to variations in money supply, income, interest rates, and money demand. Expectations of asset holders concerning future exchange rates are influenced by beliefs regarding future monetary policy (Mussa, 1976). From this perspective, the equilibrium rate is directly related to the instruments of monetary policy. The monetary model also implies that speculation may be a significant factor affecting exchange rates (Bilson, 1978).

Gross domestic product (GDP) may also be related to exchange rate fluctuations. Dritsakis (2004) presents evidence that there is a causal relationship between exchange rates and economic growth in Greece. Price levels decrease with the increase of economic growth (real gross domestic product growth) and the decline of the price level (relative to price levels in other countries) results in appreciation of the domestic currency. Thus, there is a positive relationship between economic growth and real appreciation of exchange rate. As another example of this phenomenon, East Asia experienced high per capita GDP growth and real currency appreciations in the period from 1973 to 1995 (Ito et al., 1999). These studies indicate that GDP may influence exchange rate dynamics in Bangladesh.

Hoffman and MacDonald (2009) note that real exchange rates and real interest rates have economically significant relationships. Higher interest rates attract foreign capital and cause exchange rates to appreciate. Because interest rates affect the behavior of exchange rates, it is often an important variable category for analyzing exchange rate dynamics.

Purchasing Power Parity (PPP) helps explain the evolution of exchange rates over time. Inflation in the domestic country leads to depreciation of the national currency, other things equal. Exchange rate models based on PPP tend to be valid for the long run (Sarno and Taylor, 2002; Makin, 2009). However, the PPP relationship often fails to adequately represent exchange rate behavior in the short run (Edison, 1987). Rogoff (1996) notes that both long-run and short-run forces affect exchange rate dynamics. Therefore, models that take into account both long-run and short-run exchange rate dynamics can be useful.

Granger (1981) provides a framework for specifying econometric models of cointegrating and error correction relationships. Studies using cointegration and error correction approaches have found that long-run and short-run factors significantly affect financial variables (Engle and

Granger, 1987; Modeste and Mustafa, 1999). There may also be benefits to incorporating both long-run and short-run factors into models of exchange movements for currencies such as the taka.

MacDonald and Taylor (1993) note that using long-run monetary model restrictions in a dynamic error correction framework leads to exchange rate forecasts that are superior to those generated by a random walk forecast model. Similarly, Reinton and Ongena (1999) find that error correction exchange rate models developed for the Norwegian currency market outperform random walk currency predictions. Kim and Mo (1995) estimate long-run forecasts of the dollar/DM exchange rate using a multivariate cointegration model. The random walk model outperforms the structural models in the short run, but the error correction model surpasses the random walk in the long run.

According to Moosa and Burns (2013), the out-of-sample forecasting performance of exchange rate models based on monetary constructs depends partly on the forecast evaluation methodology employed. Such models outperform random walks when forecast accuracy is measured by the ability of the model to predict the direction of change. Moreover, macroeconomic models of exchange rates outperform random walks when forecast quality is measured in terms of economic value, defined as the profitability of decisions guided by the forecasts. Profitability is found to be more closely related to directional accuracy than to the magnitudes of forecast errors (Moosa and Burns, 2014; Moosa and Vaz, 2015).

In Bangladesh, inflation, GDP growth, interest rates, and current account balances have been found to influence the exchange rate (Chowdury and Hossain, 2014). Foreign exchange reserves and monetary variables have also been documented as affecting real exchange rates in Bangladesh (Uddin, Quaosar and Nandi, 2013). It should be noted that the exchange rate system of Bangladesh changed from a fixed rate to a managed float in 1979 and from managed floating to

clean floating by creating a fully convertible current account in 2003. Interestingly, these changes in the exchange rate regime are not found to have impacted the value of Bangladeshi currency in statistically significant ways (Priyo, 2009).

Nominal exchange rate models based on balance of payments and monetary constructs can be estimated within an error correction framework (Fullerton, Hattori, and Calderon, 2001; Fullerton and Lopez, 2005). Relatively little research exists on the long-run and short-run dynamics of the nominal exchange rate of Bangladesh. This study analyzes the behavior of the nominal taka/dollar exchange rate using annual data from 1976 to 2015 within an error correction framework. In addition to in-sample estimation diagnostics, out-of-sample forecasting analysis is used to provide additional evidence regarding model reliability.

Chapter 3: Theoretical Framework

This study analyzes annual frequency exchange rate data of Bangladesh using an approach similar to that employed by Fullerton and Lopez (2005) to model the Mexican peso / US dollar exchange rate. The approach incorporates several different variables that have proven helpful in analyzing exchange rate dynamics and examines the effects of both long-run and short-run forces on the exchange rate (Rogoff, 1996). Two basic frameworks are employed: a balance of payment approach depicting the effect of international reserves on exchange rate dynamics and a monetary approach. Equations (1) and (2) correspond to the balance of payments approach (Dornbusch and Fisher, 1980). Table 0 lists variable mnemonics and definitions.

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

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

Table 0: Variable Definitions

Variable	Definition
s	Natural logarithm of the nominal exchange rate.
p	Natural logarithm, Bangladesh GDP implicit price deflator, 2005=100.
p*	Natural logarithm, United States GDP implicit price deflator, 2005=100.
r_{cd}	3-6 month scheduled bank fixed deposit rate, Bangladesh.
r_{cd}^*	3-month Certificate of Deposit rate, United States.
IR	Natural logarithm, liquid international reserves, Bangladesh.
m	Natural logarithm, M2 money supply, Bangladesh.
m*	Natural logarithm, M2 money supply, United States.
y	Natural logarithm, Bangladesh real GDP, 2005 base year.
y*	Natural logarithm, United States real GDP, 2005 base year.
u	Balance of payments approach equilibrium error term.
w	Monetary approach equilibrium error term.
v	Balance of payments approach white noise random disturbance.
z	Monetary approach white noise random disturbance.
d	Difference operator.
t	Time period index.
*	Denotes foreign country variable, United States.

Equation (1), which captures long-run equilibrium dynamics, 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 and t is a time subscript. All the other explanatory variables correspond to Bangladesh. Slope coefficients represent the effects that the explanatory variables have on the taka / dollar exchange rate.

In Equation (1), a_1 is hypothesized to be positive. That is because an increase in the Bangladeshi price level relative to the United States price level is expected to reduce the value of the taka relative to the dollar, thus resulting in a higher taka / dollar exchange rate. The coefficient a_2 is hypothesized to be negative. An increase in domestic interest rates relative to foreign interest rates attracts foreign capital and causes the domestic currency to appreciate, thus decreasing the exchange rate, s. According to orthodox theory, rising international reserves increase the value of the domestic currency, which results in a negative value for a_3.

The short-run behavior of the exchange rate is represented by Equation (2). This is also the error correction equation. In this equation, the nominal taka/dollar exchange rate, price level, interest rate, and international liquid reserves variables are first-differenced and a one period lag of the stochastic error term (u_{t-1}) is included. Here, d is the 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 are incorporated into Equation (2) through the lagged residuals, u_{t-1}, from Equation (1).

The following hypotheses are advanced for the price and interest rate differential coefficients in Equation (2): $b_1 > 0$ and $b_2 < 0$. As in the long-run equation, the rationale for these

hypotheses is that higher relative price levels in Bangladesh lead to an increase in the taka/dollar exchange rate, s, while higher relative interest rates lead to a decrease in s. Also, as previously mentioned, liquid reserves are expected to have a negative effect on the exchange rate, hence, $b_3 < 0$. The error correction coefficient, b_4, measures the speed of adjustment to any deviation from long-run equilibrium. The coefficient b_4 is, accordingly, hypothesized to be negative because deviations from equilibrium will be followed by compensating adjustments in subsequent periods.

The second framework considered is based on the monetary approach of exchange rate determination (Baillie and Selover, 1987).

$$s_t = c_0 + c_1 (p – p^*)_t + c_2 (r - r^*)_t + c_3 (m – m^*)_t + c_4 (y – y^*) + w_t \quad (3)$$

$$ds_t = f_0 + f_1 d(p – p^*)_t + f_2 d(r-r^*)_t + f_3 d(m-m^*) + f_4 d(y-y^*) + f_5 w_{t-1} + z_t \quad (4)$$

In Equation (3), slope coefficients c_1, c_2, c_3 and c_4 capture the response of the nominal exchange rate to movements in national price levels, interest rates, national money supplies (m), and real gross domestic products (y), respectively. The exchange rate, price, money supply, and gross domestic product variables are expressed in natural logarithms. Equation (4) depicts the short-run behavior of the nominal exchange rate. The long-run error term is denoted by w_t and z_t is the short-run random disturbance. The one-year lag of the long-run error term is denoted w_{t-1} and f_5 represents the rate at which disequilibria from prior periods dissipate.

Expected coefficient signs for Equation (3) are $c_1 > 0$, $c_3 = 1$, and $c_4 < 0$ due to the following reasons. Higher domestic price levels relative to the foreign price level cause depreciation of the domestic currency. Moreover, the response of the exchange rate to the money supply differential is hypothesized to be unit-elastic (Baillie and Selover, 1987). A higher money supply typically leads to inflation, which tends to decrease the domestic currency value. A rise in inflation also

reduces real output, when nominal output is held constant. Hence, lower real output is associated with domestic currency depreciation and a higher exchange rate s, other things equal.

There is some ambiguity associated with the sign of c_2. According to conventional theory, higher interest rates attract foreign capital and cause the domestic currency to appreciate. If that is the case then c_2 is expected to be less than 0. However, in the sticky price model of Dornbusch (1976), $c_1 > 0$ and $c_2 = 0$. Alternate model structures have other signs for c_2. According to Kim and Mo (1995), under a flexible price framework, $c_2 > 0$.

The hypotheses for Equation (4) are largely similar to those advanced for Equation (3). Increases in both the domestic price level and the domestic money supply relative to those of the foreign country decrease the domestic currency value. Conversely, higher relative interest rates and real output levels in the home country tend to increase the domestic currency value. Furthermore, f_5 is expected to be negative because deviations from equilibrium will be followed by offsetting adjustments in subsequent periods. Therefore, expected signs for Equation (4) are $f_1 > 0$, $f_3 > 0$, $f_4 < 0$, and $f_5 < 0$. However, there is some ambiguity with respect to the sign of f_2. Dornbusch (1976) indicates that $f_2 < 0$, while Kim and Mo (1995) conjectures that $f_2 > 0$.

An autoregressive distributed lag (ARDL) modeling approach is used to establish the exact form of the model specification. A bounds testing procedure is applied to determine whether the variables in Equation (1) are cointegrated (Pesaran and Shin, 1998; Pesaran et al., 2001). This approach has been used to analyze the effect of exchange rate volatility on US exports to the rest of the world (De Vita and Abbott, 2004). The advantage of the bounds testing approach is that it does not require all of the potentially cointegrated variables be I(1), but rather allows for cases in which the variables are I(0), I(1), or a mix of the two. Moreover, its small sample properties are relatively favorable (Narayan, 2005).

The ARDL specification of Equation (1) is shown in Equation (5). The optimal number of lags for each variable can be selected using the Akaike Information Criterion or the Schwarz Bayesian Criterion (Enders, 2010).

$$s_t = \alpha_0 + \sum \Upsilon_i s_{t-i} + \sum \alpha_{1i} (p - p^*)_{t-i} + \sum \alpha_{2i} (r - r^*)_{t-i} + \sum \alpha_{3i} IR_{t-i} + u_t \quad (5)$$

In Equation (5), i is an index for lags, p is the optimal number of lags of the dependent variable, q_j is the optimal number of lags for each explanatory variable, and u_t is an error term. In Equation (6), long-run coefficients are calculated using the estimated α_{ji} parameters, where j is an index identifying the explanatory variables employed in the model. The long-run coefficients are then substituted into Equation (1) and the residuals, u_t, are calculated. The lagged residuals, u_{t-1}, will be included in the short-run error correction equation if a cointegrating relationship exists.

$$a_j = \sum \alpha_{ji} / (1- \sum \Upsilon_i) \quad (6)$$

A bounds test is conducted to determine whether the variables in Equation (1), for the balance of payments approach, are cointegrated (Pesaran et al, 2001). For this test Equation (7) is estimated, where d denotes the first-difference and v is a random error term.

$$ds_t = \rho_0 + \sum \theta_i ds_{t-i} + \sum \rho_{1i} d(p - p^*)_{t-i} + \sum \rho_{2i} d(r - r^*)_{t-i} + \sum \rho_{3i} d(IR)_{t-i} + \rho_4 s_{t-1} + \rho_5 (p - p^*)_{t-1} + \rho_6 (r - r^*)_{t-1} + \rho_7 IR_{t-1} + v_t \quad (7)$$

The null hypothesis is that there is no cointegration. An F-test can be used to evaluate the null hypothesis, which can be formally stated as H_0: $\rho_4 = \rho_5 = \rho_6 = \rho_7 = 0$. There is one set of (lower-bound) critical values for the case where all variables are I(0) and another set of (upper-bound) critical values for the case where all variables are I(1) (Pesaran et al, 2001). When the calculated F-statistic is larger than the upper bound, then null hypothesis can be rejected, which indicates that there is cointegration. If the F-statistic falls between the upper and lower critical values, then the conclusion of the test is indeterminate.

Equation (8) is the estimated short-run error correction equation. Short-run departures from the long-run equilibrium can happen due to various types of economic and non-economic shocks. When those shocks occur, the exchange rate is hypothesized to respond in a manner that allows the equilibrium to eventually be re-attained. The specification for the short-run exchange rate equation is shown in Equation (8). The right hand side variable lags are equal to those in the long run equation minus one, except when zero lags are included in the long run equation for a variable in which case the short run equation also has zero lags for that variable.

$$ds_t = \beta_0 + \sum\delta_i\, d_i\, s_{t-i} + \sum p_{1i}\, d(p - p^*)_{t-i} + \sum p_{2i}\, d(r - r^*)_{t-i} + \sum p_{3i}\, d(IR)_{t-i} + \varphi\, u_{t-1} + v_t \qquad (8)$$

The coefficient for the error term, u_{t-1}, is expected to be negative, and indicates the rate at which a short-run departure from equilibrium will dissipate. The time required for complete adjustment to the long-run equilibrium increases as the value of the error term coefficient approaches zero.

In order to determine whether the variables in Equation (3), for the monetary approach, are cointegrated, an ARDL model is estimated and the bounds testing procedure is again applied (Pesaran and Shin, 1998; Pesaran et al., 2001). The ARDL specification of Equation (3) is shown in Equation (9), where i is an index for lags w_t is an error term.

$$s_t = \mu_0 + \sum \eta_i\, s_{t-i} + \sum \mu_{1i}\, (p - p^*)_{t-i} + \sum \mu_{2i}\, (r - r^*)_{t-i} + \sum \mu_{3i}\, (m - m^*)_{t-i} + \sum \mu_{4i}\, (y - y^*)_{t-i} + w_t \qquad (9)$$

In Equation (10), long-run coefficients are calculated using the estimated μ_{ji} parameters, where j is an index identifying the explanatory variables considered in the model. The long-run coefficients are then substituted into Equation (3) and the residuals, w_t, are calculated. The lagged residuals, w_{t-1}, will be included in the short-run error correction equation if a cointegrating relationship exists.

$$c_j = \Sigma\, \mu_{ji} / (1 - \Sigma\, \eta_i) \qquad (10)$$

For the bounds test, Equation (11) is estimated, where d denotes the first-difference and v is a random error term.

$$ds_t = \rho_0 + \Sigma\, \theta_i\, ds_{t-i} + \Sigma\, \rho_{1i}\, d(p - p^*)_{t-i} + \Sigma\, \rho_{2i}\, d(r - r^*)_{t-i} + \Sigma\, \rho_{3i}\, d(m - m^*)_{t-i} + \Sigma\, \rho_{4i}\, d(y - y^*)_{t-i} + \Sigma\, \rho_5\, s_{t-1} + \rho_6\, (p - p^*)_{t-1} + \rho_7\, (r - r^*)_{t-1} + \rho_8\, (m - m^*)_{t-1} + \rho_9\, (y - y^*)_{t-1} + v_t \quad (11)$$

The null hypothesis is no cointegration, hence, H_0: $\rho_5 = \rho_6 = \rho_7 = \rho_8 = \rho_9 = 0$. Calculated F-statistics can be compared against the critical values presented in Pesaran et al. (2001) to determine whether cointegration is present.

Equation (12) is the estimated short-run error correction equation. Short-run departures from the long-run equilibrium can happen due to a variety of factors. The right hand side variable lags are equal to those in the long run equation minus one, except when zero lags are included in the long run equation for a variable in which case the short run equation also has zero lags for that variable.

$$ds_t = \beta_0 + \Sigma\, \delta_i\, ds_{t-i} + \Sigma\, \rho_{1i}\, d(p - p^*)_{t-i} + \Sigma\, \rho_{2i}\, d(r - r^*)_{t-i} + \Sigma\, \rho_{3i}\, d(m - m^*)_{t-i} + \Sigma\, \rho_{4i}\, d(y - y^*)_{t-i} + \varphi\, w_{t-1} + z_t \quad (12)$$

The coefficient for the error term, w_{t-1} is expected to be negative, and indicates the rate at which a short-run departure from equilibrium will dissipate.

Once the model has been developed, forecasts are generated to examine out-of-sample predictive precision. The dataset used for estimation purposes runs from 1976 to 2015. In order to provide an adequate number of observations for statistical analysis of forecast accuracy, multiple sets of forecasts are generated from that dataset. In the first step, the models are estimated using data from 1976 to 2006 and the three-year ahead forecast period runs from 2007 to 2009. Subsequently, the estimation period is extended by one year and the forecast period covers 2008

to 2010. This process is repeated multiple times until the forecast period runs from 2013 to 2015. This results in a total of 21 forecast observations.

In order to evaluate forecast accuracy, it is common to use Theil U-statistics based on the root-mean squared error (Theil, 1961). U-statistics are constrained to fall between 0 and 1, where a value of zero indicates the best possible fit is attained (Pindyck and Rubinfeld, 1998). In addition to U-statistics, the null hypothesis that the ARDL forecasts are no more accurate than random walk (RW) forecasts is also examined using two statistical tests.

For the first test, proposed by Diebold and Mariano (1995), the forecast error differential can be defined as $d_t = MSE(e_{RWt}) - MSE(e_{ARDLt})$, where $MSE(e_{RWt})$ and $MSE(e_{ARDLt})$ are mean squared error statistics for the RW and ARDL forecasts, respectively. The null hypothesis is that both sets of forecasts are equally accurate, which is equivalent to the hypothesis that the population mean of the differential variable is equal to zero as shown in Equation (13).

$$H_0: \mu(d) = 0 \tag{13}$$

The Diebold and Mariano (DM) statistic is expressed in Equation (14), where $\bar{d}$ is the sample mean of d_t and $\hat{V}(\bar{d})$ is the variance of $\bar{d}$.

$$DM = \frac{\bar{d}}{\sqrt{\hat{V}(\bar{d})}} \tag{14}$$

A positive value of the DM statistic implies that the ARDL forecasts are more accurate than the RW benchmarks. A one-tailed test with critical values from a normal distribution can be used to determine whether the difference in accuracy is statistically significant (Kilian and Taylor, 2003).

Next, an error differential regression test is also used to examine the relative accuracies of the forecasts (Ashley, Granger, and Schmalensee, 1980). The null hypothesis is again that the mean squared error (MSE) of the RW forecast errors (e_{RW}) is equal to the MSE of ARDL forecast

errors (e_{ARDL}). The null hypothesis is expressed in Equation (15) by defining two new variables, Δ_t and Σ_t.

$$\Delta_t = e_{RWt} - e_{ARDLt} \text{ and } \Sigma_t = e_{RWt} + e_{ARDLt}$$

$$H_0 : MSE(e_{RW}) - MSE\ (e_{ARDL}) = [\mu\ (e_{RW})^2 - \mu\ (e_{ARDL})^2] + cov\ (\Delta, \Sigma) = 0 \quad (15)$$

In Equation (15), cov stands for covariance and μ denotes the means of the forecast errors.

The null hypothesis is tested using regression equations as shown in Equations (16) and (17). Equation (16) yields the specification for testing the null hypothesis when the error means have the same sign and Equation (17) is employed when the error means have opposite signs.

$$\Delta_t = \beta_1 + \beta_2 [\Sigma_t - m\ (\Sigma_t)] + u_t \quad (16)$$

$$\Sigma_t = \beta_1 + \beta_2 [\Delta_t - m\ (\Delta_t)] + u_t \quad (17)$$

In Equation (16) and Equation (17), u_t is a randomly distributed error term and the signs of β_1 and β_2 indicate which set of forecasts is more accurate. Decision rules for determining whether to reject the null hypothesis based on t-statistics and F-statistics are given in Ashley, Granger, and Schmalensee (1980).

A directional accuracy analysis is also employed to evaluate predictive accuracy. In this approach, statistical tests are employed to determine whether the forecasts accurately predict the direction of change (i.e., increases versus decreases) in the exchange rate. A contingency table, such as Table 1, helps to evaluate directional accuracy.

Table 1: Contingency table to evaluate directional accuracy

		Forecast		
		Increase	**Decrease**	**Total**
Actual	**Increase**	n_{11}	n_{12}	n_{10}
	Decrease	n_{21}	n_{22}	n_{20}
	Total	n_{01}	n_{02}	N

The total number of forecasts is represented by N and correct predictions are denoted by the diagonal elements, n_{11} and n_{22}. If directional changes are correctly predicted in all instances, the off-diagonal elements, n_{12} and n_{21}, will both equal zero.

Table 1 can be modified by expressing the values in each cell in terms of probabilities. Table 2 shows a probability value contingency table where the probabilities are calculated by dividing the numbers in each row by the row totals. If the forecasts always correctly predict the direction of change, $p_{11} = 1$ and $p_{22} = 1$, while the off-diagonal probabilities equal zero.

Table 2: Probability value contingency table

		Forecast		
		Increase	**Decrease**	**Total**
Actual	**Increase**	p_{11}	$1-p_{11}$	$p_{10} = 1$
	Decrease	$1-p_{22}$	p_{22}	$p_{20} = 1$

Pesaran and Timmermann (1994) propose a test of the null hypothesis that actual and predicted directional changes are independently distributed. Equation (18) is the null hypothesis for an m by m probability value contingency table, where m is any positive integer.

$$H_0: \Sigma_{i=1}^{m} (p_{ii} - p_{i0}p_{0i}) = 0 \quad (18)$$

The test involves calculating two new variables based on a contingency table like Table 1. The first variable, $\widehat{\mathrm{P}}$, is the proportion of times that the direction of change is correctly forecasted and the second variable is $\widehat{P}_*$, is the proportion of correct predictions that would be expected if the forecasted directional changes were distributed independently of the actual observed directional change. The variance of these two variable must be computed to construct the test statistics shown in Equation (19).

$$\mathrm{PT} = \frac{\widehat{\mathrm{P}} - \widehat{\mathrm{P}}_*}{\sqrt{\mathrm{var}(\widehat{\mathrm{p}}) - \mathrm{var}(\widehat{\mathrm{P}}_*)}} \sim \mathrm{N}(0, 1) \qquad (19)$$

If the computed Pesaran-Timmermann (PT) statistic is higher than the 5% critical value for a one-sided normal test, then the null hypothesis can be rejected, which implies that the forecasts provide useful information on the direction of change (Granger and Pesaran, 2000).

The following section describes data and empirical results. Annual-frequency data covering the 1976 to 2015 sample period are used to analyze the behavior of the nominal taka/dollar exchange rate. Two models are developed to investigate nominal exchange rate dynamics within an error correction framework. Those models are based on balance of payments and monetary constructs (Fullerton, Hattori, and Calderon, 2001). Autoregressive distributed lag (ARDL) models are estimated and bounds testing is conducted to determine whether cointegration exists among the variables included in each model. Finally, forecasts are generated and formal accuracy tests are conducted.

Chapter 4: Data and Empirical results

Data for domestic (Bangladesh) and foreign (United States) variables are collected from the International Monetary Fund database *International Financial Statistics 2013* and from the website of the International Monetary Fund (IMF). Annual data from 1976 to 2015 are collected for the taka / dollar exchange rate and for the independent variables employed in the balance of payments and monetary construct equations. Variable definitions and data sources are provided in Table 3. Real gross domestic products (GDP) for both countries are the proxy variables for real incomes. Because data on certificate of deposit interest rates for the United States are truncated in 2010, non-jumbo deposit interest rates are used for 2011 to 2015.

Table 3: Variable Definitions and Data Sources

Variable	Definition, Units, and Sources
s	Natural logarithm of the nominal exchange rate (taka/dollar). Source: 2016 IMF *International Financial Statistics CD-ROM* and IMF Website.
p	Natural logarithm, Bangladesh GDP implicit price deflator, 2005=100. Source: 2016 IMF *International Financial Statistics CD-ROM* and IMF website.
p*	Natural logarithm, United States GDP implicit price deflator, 2005=100. Source: 2016 IMF *International Financial Statistics CD-ROM* and IMF website.
r_{cd}	3-6 month scheduled bank fixed deposit rate, Bangladesh. Source: 2016 IMF *International Financial Statistics CD-ROM* and IMF website.
r_{cd}*	3-month Certificate of Deposit rate, United States. Source: 2016 IMF *International Financial Statistics CD-ROM* and IMF website.
IR	Natural logarithm, liquid international reserves, Bangladesh. Millions US dollars. Source: 2016 IMF *International Financial Statistics CD-ROM* and IMF website.

m	Natural logarithm, M2 money supply, Bangladesh, National currency (Taka). Source: 2016 IMF *International Financial Statistics CD-ROM* and IMF website.
m*	Natural logarithm, M2 money supply, United states, billions of dollars. Source: 2016 IMF *International Financial Statistics CD-ROM* and IMF website.
y	Natural logarithm, Bangladesh real GDP, 2005 base year. Billions national currency (Taka). Source: 2016 IMF *International Financial Statistics CD-ROM* and IMF website.
y*	Natural logarithm, United States real GDP, 2005 base year. Billions of dollars. Source: 2016 IMF *International Financial Statistics CD-ROM* and IMF website.
u	Balance of payments approach equilibrium error term.
w	Monetary approach equilibrium error term.
v	Balance of payments approach white noise random disturbance.
z	Monetary approach white noise random disturbance.
d	Difference operator.
t	Time period index.
*	Denotes foreign country variable, United States.

Several studies based on the application of time series methodologies have been completed using relatively few observations (Shiller and Perron 1985; Hakkio and Rush 1991). Research in this area indicates that empirical analyses conducted for short time spans should use lower numbers of time lags to avoid pronounced losses in test power (Zhou, 2001). This issue is examined below.

The ARDL balance of payments models are summarized in Tables 4 and 5 and monetary construct models are summarized in Tables 6 and 7. The ARDL approach is not appropriate to use for variables that are integrated of an order greater than one (Pesaran et al., 2001). Augmented Dickey-Fuller unit root tests indicate that all the variables included in the two models are either I(0) or I(1). Thus, the data are suitable for analysis within the ARDL framework.

The Akaike information criterion is utilized for lag length selection in developing the ARDL models for the taka / dollar exchange rate. A maximum of three lags of each variable is

considered for inclusion in the final specifications. The minimum values of the Akaike information criterion correspond to an ARDL (2, 1, 0, 2) balance of payments model and an ARDL (2, 3, 0, 0, 0) monetary construct model. The first number in parentheses is the number of dependent variable lags included in the final specifications and the subsequent numbers are the lag orders for each of the explanatory variables. The Appendix reports alternative models selected on the basis of the Akaike information criterion when the maximum number of lags considered is restricted to one or two.

Table 4 reports estimated long-run elasticities plus diagnostic statistics for the ARDL (2, 1, 0, 2) balance of payments model of the taka / dollar exchange rate. For the model presented in Table 4, the Akaike information criterion and Hannan-Quinn criterion are -3.9 and -3.76 respectively, which are lower than the corresponding information criteria in Table A1 and the ARDL (2, 1, 0, 2) model performs better than the model with a maximum of one lag. Furthermore, the same specification (2, 1, 0, 2) is selected regardless of whether the maximum lag order is set at two or three. A Chi-squared autocorrelation function test indicates that serial correlation is not problematic. The calculated F-statistic for H_0: $\rho_4 = \rho_5 = \rho_6 = \rho_7 = 0$ is 8.35, which exceeds the 5-percent critical value for the upper bound computed by Narayan (2005). This confirms that the variables of the model are cointegrated.

According to Table 4, the long-run coefficient signs align with the hypothesized signs. The price elasticity of the exchange rate is 1.68, which implies that, as the domestic price level increases by 1% relative to the United States price level, the domestic currency depreciates 1.68%. This estimate is smaller than the coefficient of the relative price levels, 2.42%, indicated by Meerza (2012) in a study of the taka per dollar exchange rate. Chowdhury and Hossain (2014) report that the coefficient of the inflation rate in the exchange rate model is 0.71. That suggests that the

inflation rate and the exchange rate are positively correlated in Bangladesh and, as hypothesized, an increase of the domestic price level relative to the USA price level will increase the exchange rate. Mark (1990) also finds that there is a positive relationship between the domestic price level and the exchange rate.

Moreover, higher domestic interest rates tend to attract foreign investment. The interest rate coefficient is -0.04, which indicates that an increase in the Bangladesh-US interest rate differential of 1 point will lead the taka to appreciate by 4% against the dollar. That is greater in absolute value than the -0.0005 estimate reported by Priyo (2009) in a previous exchange rate study for Bangladesh. The coefficient sign corroborates conventional economic theory, which holds that, as the domestic interest rate rises relative to foreign interest rates, more foreign investors invest in domestic financial securities and the inflow of foreign currency leads to appreciation of the domestic currency.

Furthermore, the international liquid reserve elasticity of the exchange rate is -0.22, which indicates that, if international liquid reserves increase by 1%, then the taka appreciates relative to the dollar by 0.22%. Uddin et al. (2013) estimates that the foreign exchange reserve elasticity of the exchange rate is -0.0975, which implies that a 1% increase of foreign exchange reserves results in a relatively small appreciation of the taka by only 0.0975%. In both studies, an increase of foreign exchange reserves occurs as a result of net inflows denominated in foreign currencies, and leads to appreciation of the domestic currency value. Although the sign and magnitude of the international reserve coefficient in Table 4 seem plausible, it is not significantly different from zero at the 5% level.

Table 4: ARDL Analysis of Exchange Rate Results using Balance of Payments Approach

Long Run Coefficients for ARDL(2, 1, 0, 2) model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
c	6.219976	1.856375	3.350604	0.0023
p - p*	1.683982	0.617939	2.725157	0.0108
r - r*	-0.040923	0.030371	-1.347438	0.1883
IR	-0.216184	0.210334	-1.027813	0.3125

Diagnostic statistics for the underlying ARDL model

R-squared	0.996930	Mean dependent var	3.740686
Adjusted R-squared	0.996083	S.D. dependent var	0.496316
S.E. of regression	0.031063	Akaike info criterion	-3.902212
Sum squared resid	0.027982	Schwarz criterion	-3.514362
Log likelihood	83.14202	Hannan-Quinn criter.	-3.764218
F-statistic	1177.091	Durbin-Watson stat	1.762757
Prob(F-statistic)	0.000000		

Chi-squared autocorrelation function Q-test for higher order autocorrelation

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	0.112	0.112	0.5182	0.472
		2	-0.080	-0.094	0.7868	0.675
		3	-0.102	-0.084	1.2401	0.743
		4	-0.084	-0.072	1.5557	0.817

Bounds test results

ARDL Bounds Test

Test Statistic	Value	k
F-statistic	8.349400	3

Critical Value Bounds

Significance	I0 Bound	I1 Bound

10%	2.37	3.2
5%	2.79	3.67
2.5%	3.15	4.08
1%	3.65	4.66

Note: Bounds test critical values are from Narayan (2005).

Additionally, CUSUM and CUSUMSQ tests are carried out to determine whether the estimated parameters remain stable or change significantly over time. The calculated CUSUM statistics are inside the 5-percent critical bounds as shown in Figure 1. Figure 2 shows that the CUSUMSQ statistics exceed the 5-percent critical bounds very slightly for a small subset of the time periods considered but otherwise remain well inside the bounds. These results indicate that the estimated parameters are reasonably stable over the time.

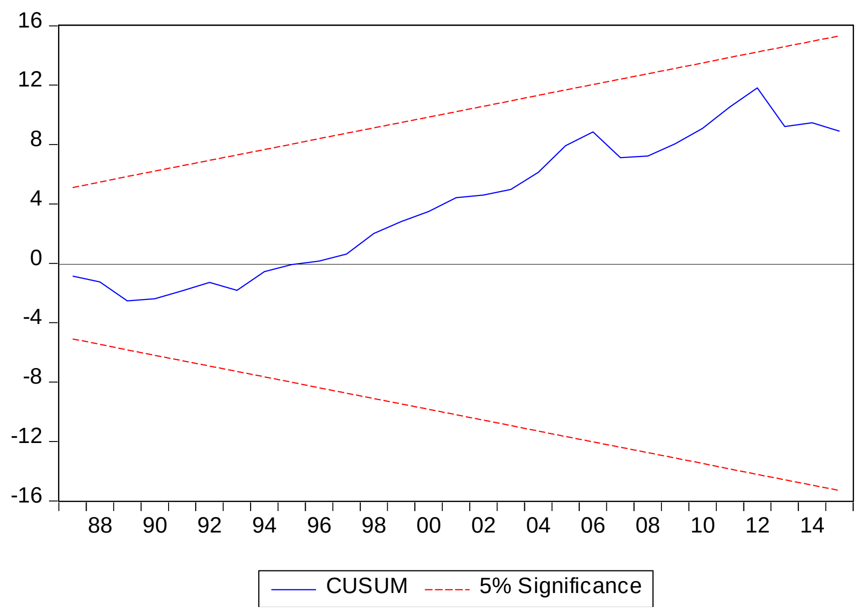

Figure 1: CUSUM results for exchange rate based on balance of payments

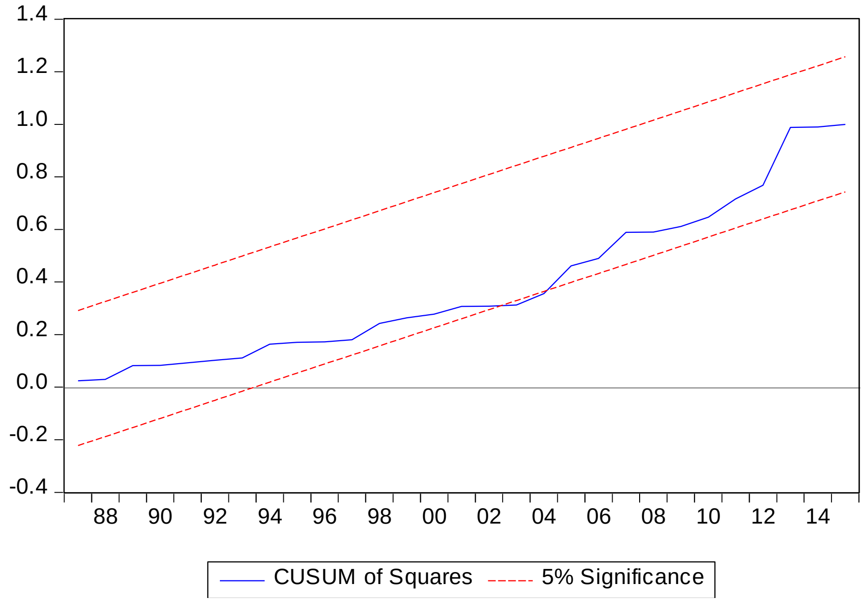

Figure 2: CUSUMSQ results for exchange rate based on balance of payments

Short-run error correction estimation results for the ARDL (2, 1, 0, 2) balance of payments model are summarized in Table 5. A chi-squared autocorrelation function Q-test indicates that serial correlation is not problematic. The coefficient of the lagged exchange rate is 0.28. This indicates that, after accounting for the impacts of the independent variables included in the model, a 1% increase in the exchange rate in the previous year is associated with a 0.28% increase in the current year. The estimated coefficient is considerably lower than the 1.41 response documented by Uddin et al. (2013) and it suggests that short-run inertial forces are relatively subdued for the sample period utilized in this study. Moreover, the associated t-statistic of the one-period lag of the exchange rate exceeds the 5% critical value.

The short-run price level elasticity of the exchange rate is -0.12, indicating that a 1% increase of the domestic price level relative to the United States price level will cause the taka to appreciate by 0.12% against the dollar. This outcome is counterintuitive. However, Meerza

(2012) also finds a similar relationship in the short-run between the exchange rate and the price differential in a study of Bangladesh currency markets. According to Meerza (2012), the coefficient of the inflation differential with a lag of one period is -0.35, substantially more elastic than the coefficient reported in Table 5. The parameter estimate in Table 5, however, fails to satisfy the 5% significance criterion. The short-run link between inflation and the taka / dollar exchange rate appears weak, at best.

The interest rate coefficient is -0.002, which indicates that a 1 point increase in the domestic-foreign interest rate differential decreases the exchange rate by 0.2%. This outcome is less, in terms of absolute value, than the -0.77% effect reported by AbuDalu et al. (2008) in a short-run exchange rate model for Singapore currency markets. The negative sign of the interest rate parameter estimate reported in Table 5 aligns with the hypothesis. This outcome is economically plausible because an increase in the domestic interest rate relative to the foreign interest rate encourages foreign investment, which increases foreign currency inflow and leads to appreciation of the domestic currency. However, the associated t-statistic does not surpass the 5% critical value.

The short-run coefficient of contemporaneous liquid international reserves (IR) is -0.012 and that for liquid international reserves (IR) with a one-period lag is -0.043. These outcomes both have the hypothesized sign. This means, that when the liquid reserve ratio increases by 1%, then the domestic currency value appreciates by 0.012% in the first year, and by 0.043% in the next year. This outcome makes sense because the increment of dollar inflows increases the foreign exchange reserves, which appreciates the domestic currency value. The estimated effects are greater in absolute value than the -0.002% impact of international reserves reported by Ahmed et al. (2012) in a study of the Pakistani Rupee per United States dollar exchange rate. Although these outcomes are for two different countries, the coefficient of IR reported in Table 5 seems more

plausible because economic theory suggests that an increment in liquid international reserves affects the exchange rate directly and this effect is more pronounced in the Table 5 estimates than in the study by Ahmed et al. (2012). Therefore, there is a negative relationship between exchange rate and international reserves in the short-run.

As hypothesized, the sign for the error correction parameter (u_{t-1}) is less than zero. The value of the error coefficient is -0.09, which indicates 11 years (1/0.09) are needed for short-run departures from equilibrium to fully dissipate. This is substantially slower than the speed of adjustment documented by Meerza (2012) in a prior exchange rate study for Bangladesh. According to that study, 7 years (1/0.14) are needed for short-run departures from equilibrium to fully dissipate. Both studies indicate that short-run deviations from the long-run taka / dollar equilibrium exchange last for fairly long periods of time.

One potential explanation for the existence of long lasting disequilibria in the currency markets of Bangladesh lies in the fact that the country had a fixed exchange rate regime from January 1972 to May 2003. That time period covers the majority of the sample period examined in this analysis. Under a fixed exchange rate regime, it generally takes longer to restore equilibrium as compared to a floating exchange rate regime where market forces operate more flexibly (Krugman and Obstfeld, 2006). A floating exchange rate regime has existed in Bangladesh only since June 2003.

Table 5: Exchange Rate Error Correction Results based on Balance of Payments Approach

Dependent Variable: d(s)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
c	0.000571	0.014079	0.040573	0.9679
d(s(-1))	0.280101	0.130200	2.151312	0.0394
d(p-p*)	-0.124439	0.072506	-1.716253	0.0961
d(r-r*)	-0.002155	0.003433	-0.627841	0.5347
d(IR)	-0.012415	0.015899	-0.780844	0.4408
d(IR(-1))	-0.043294	0.015338	-2.822703	0.0082
U_t(-1)	-0.095464	0.026827	-3.558532	0.0012

Diagnostic statistics for the underlying ARDL model

R-squared	0.687361	Mean dependent var	0.042602
Adjusted R-squared	0.626850	S.D. dependent var	0.048947
S.E. of regression	0.029900	Akaike info criterion	-4.017125
Sum squared resid	0.027713	Schwarz criterion	-3.715464
Log likelihood	83.32537	Hannan-Quinn criter.	-3.909796
F-statistic	11.35930	Durbin-Watson stat	1.758612
Prob(F-statistic)	0.000001		

Chi-squared autocorrelation function Q-test for higher order autocorrelation

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	0.112	0.112	0.5182	0.472
		2	-0.080	-0.094	0.7868	0.675
		3	-0.102	-0.084	1.2401	0.743
		4	-0.084	-0.072	1.5557	0.817

Next, an ARDL (2, 3, 0, 0, 0) model is estimated for the taka / dollar exchange rate using the monetary approach. Table 6 reports estimated long-run elasticities with diagnostic statistics for this ARDL model. This model has the lower Akaike information criterion relative to the other specifications with different lag structures. Autocorrelation Q-statistics for the first four lags indicate that serial correlation is not problematic. The calculated F-statistic for H_0: $\rho_5 = \rho_6 = \rho_7 = \rho_8 = \rho_9 = 0$ is 3.14, which is higher than the 5-percent critical value for the upper bound computed by Narayan (2005). This confirms that the variables of the model are cointegrated.

According to Table 6, the price level elasticity of the exchange rate is 0.14, which implies that 1% increases in Bangladeshi inflation relative to United States inflation increase the taka / dollar exchange rate by 0.14%. This estimate is larger than the 0.002% estimate reported by Priyo (2009), but substantially smaller than the 2.42% obtained by Meerza (2012). The positive sign of the price coefficient is in agreement with the hypothesis and with conventional economic theory. An increase in domestic inflation relative to inflation in the foreign country leads to depreciation of the domestic currency. The associated t-statistic does not, however, exceed the 5% critical value. On the basis of impulse-response analysis, Mark (1990) also finds that the long-run dynamic relationship between nominal exchange rates and relative price levels is weak.

The estimated interest rate coefficient sign contradicts the hypothesis and conventional economic theory. When the domestic interest rate increases, foreign currency inflows are also expected to increase. However, the interest rate coefficient is 0.003, which indicates that a 1 percentage point increment in the domestic-foreign interest rate differential causes the domestic currency value to depreciate by 0.3%. The estimated outcome is counter-intuitive because, as the interest rate increases, foreign currency inflows are predicted to result in appreciation of the domestic currency. However, the associated t-statistic does not surpass the 5% critical value and

the most plausible interpretation of the interest rate coefficient in Table 6 is that this variable has no discernible long-run impact on the exchange rate in Bangladesh. Some other studies of exchange rate dynamics in Bangladesh also report positive interest rate coefficients that are statistically indistinguishable from zero (Priyo, 2009; Chowdhury and Hossain, 2014).

The money supply (M2) elasticity of the exchange rate is 0.5, which indicates that a 1% increase in the money supply of Bangladesh relative to the money supply of the United States results in depreciation of the taka relative to the dollar by 0.5%. Uddin et al. (2013) find that a 1% increase in the money supply results in a real depreciation of the taka by 0.52% in Bangladesh. This outcome is logical according to economic theory, since an increase in money supply results in inflation and inflation tends to diminish the domestic currency value. In addition to the alignment of the sign of the money supply coefficient with the stated hypothesis for it, the computed t-statistic for M2 satisfies the standard significance criterion.

An increase in real output in Bangladesh with respect to real output in the United States is expected to cause the taka to appreciate relative to the dollar. According to the Table 6, the output elasticity of the exchange rate is -0.62, which indicates that if domestic output increases by 1% with respect to foreign output, then the domestic currency appreciates by 0.62%. Nieh & Wang (2005) find that the coefficient on output with a lag of one period is -0.783 in an exchange rate model developed for Taiwan. Hooper and Morton (1982) note that the output elasticity of the exchange rate is -1.46 in a model of dollar exchange rate determination in the United States.

Table 6: ARDL Analysis of Exchange Rate Results using the Monetary Approach

Long Run Coefficients for ARDL(2, 3, 0, 0, 0) model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
c	-6.481559	1.372649	-4.721936	0.0001
p - p*	0.135884	0.156813	0.866538	0.3938
r - r*	0.002653	0.006482	0.409275	0.6856
m - m*	0.503633	0.063630	7.915086	0.0000
y - y*	-0.623116	0.162121	-3.843536	0.0007

Diagnostic statistics for the underlying ARDL model

R-squared	0.996520	Mean dependent var	3.768559
Adjusted R-squared	0.995360	S.D. dependent var	0.472049
S.E. of regression	0.032155	Akaike info criterion	-3.811031
Sum squared resid	0.027917	Schwarz criterion	-3.375648
Log likelihood	80.50408	Hannan-Quinn criter.	-3.657538
F-statistic	859.0523	Durbin-Watson stat	2.251014
Prob(F-statistic)	0.000000		

Chi-squared autocorrelation function Q-test for higher order autocorrelation

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	-0.077	-0.077	0.2347	0.628
		2	-0.064	-0.070	0.4025	0.818
		3	-0.023	-0.034	0.4258	0.935
		4	-0.144	-0.155	1.3338	0.856

Bounds test results

ARDL Bounds Test

Test Statistic	Value	k
F-statistic	3.136915	4

Critical Value Bounds

Significance	I0 Bound	I1 Bound
10%	2.2	3.09
5%	2.56	3.49
2.5%	2.88	3.87
1%	3.29	4.37

Note: Bounds test critical values are from Narayan (2005).

Additionally, CUSUM and CUSUMSQ tests are carried out to examine parameter stability. Figure 3 indicates that the calculated statistics stay within the 5-percent critical bounds for the CUSUM test. Figure 4 indicates a fair degree of parameter stability, though the calculated statistics do exceed the 5-percent bounds over a subset of the sample period. This suggests that the monetary long-run parameters are relatively stable over time.

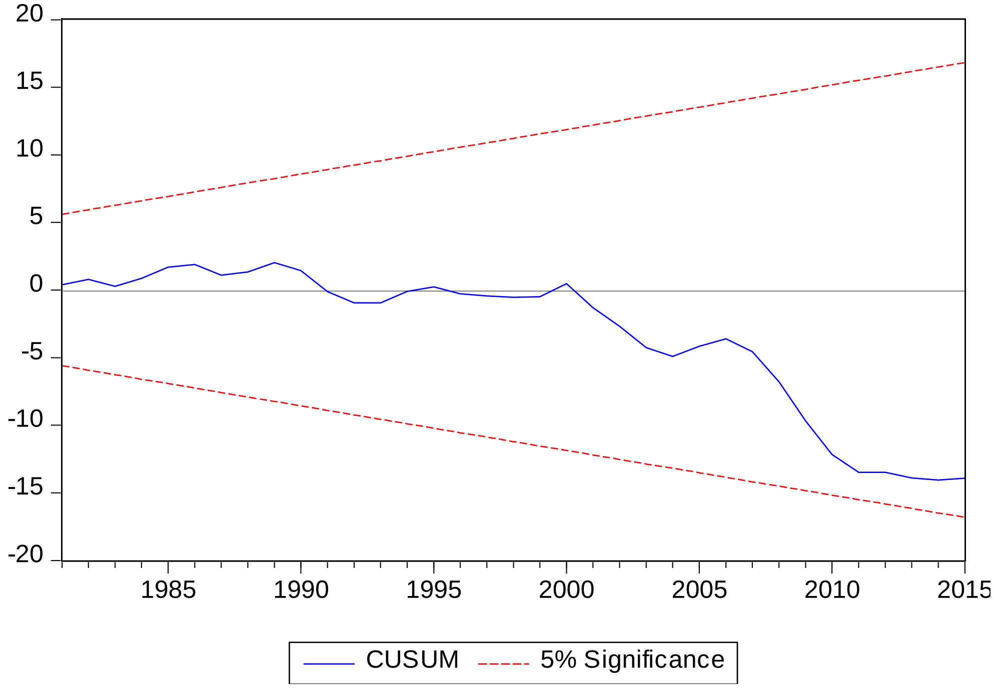

Figure 3: CUSUM results for exchange rate based on the monetary framework

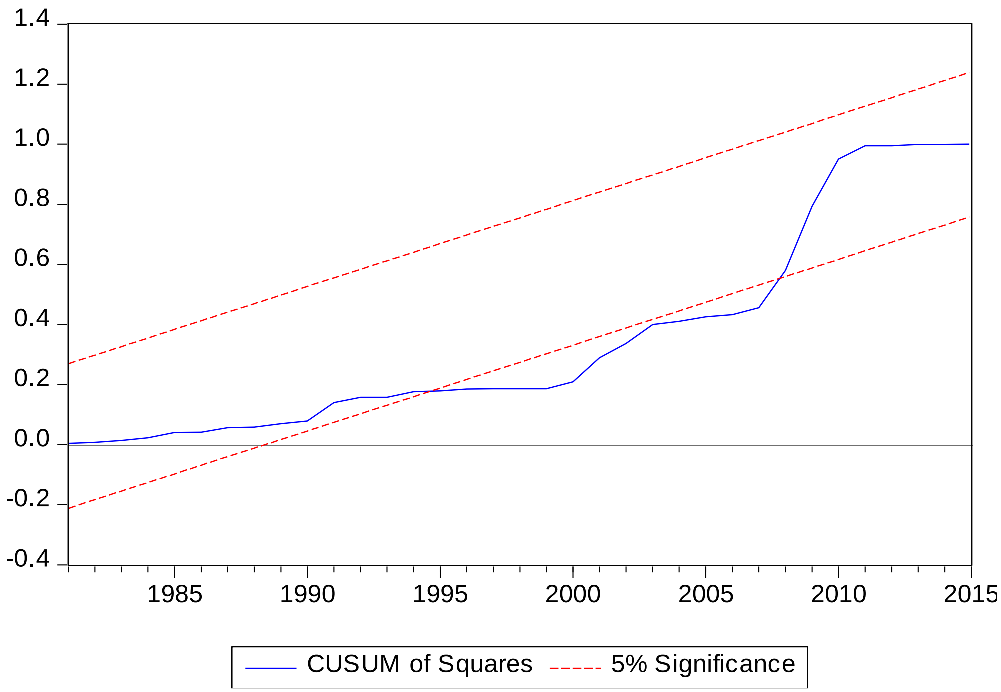

Figure 4: CUSUMSQ results for exchange rate based on the monetary framework

Table 7 displays the results for the short-run error correction equation based on the monetary approach. Chi-squared Q-statistics for the residual autocorrelation function indicate that serial correlation is not problematic for the residuals associated with Table 7. The coefficient of the lagged exchange rate is 0.54, which indicates that a 1% increase in the exchange rate is associated with a 0.54% increase in the exchange rate in the following year. This outcome is smaller than the 1.41% response documented by Uddin et al. (2013) for the taka per United States dollar exchange rate. The latter estimate implies the existence of a very large inertial component in the exchange rate series that is not corroborated by the evidence presented in this analysis. The 0.54 estimate in Table 7 implies that the exchange rate in the previous period has a more moderate impact on the exchange rate in the current period once the impacts of the other independent variables in the model have been taken into account, which is a plausible result. Moreover, Table 7 indicates that the associated t-statistic for the lagged exchange rate exceeds the 5% critical value.

The coefficients for the contemporaneous, one-year and two-year lags of the price level sum to -0.11, which indicates that a 1% increase in the domestic price level relative to the foreign price level leads to a 0.11% appreciation in the domestic currency value. This outcome contradicts the stated hypothesis. However, Meerza (2012) also finds that the coefficient of the inflation differential with a lag of one period is -0.35, which is fairly similar to the contemporaneous parameter value shown in Table 7. Even though reported in two separate studies covering different sample periods, a short-run negative relationship between the price level differential and the exchange rate is surprising. Additional research on this aspect of the currency market for the taka appears warranted.

The coefficient for the interest rate shown in Table 7 is 0.003. This outcome implies that, if the interest rate differential increases by 1 point, then the domestic currency depreciates by 0.3%

within one year. This outcome contradicts the stated hypothesis that an increase in the interest rate should attract foreign investment, which will appreciate the domestic currency value. This counter-intuitive outcome may have occurred due to political instability and sometimes excessive inflation observed in Bangladesh over the course of the sample period. Changes in the nominal interest rate reflect, among other things, changes in the expected inflation rate. In times of high inflation, the relationship between interest rates and expected inflation may be strong enough to result in a positive marginal effect of interest rates on the exchange rate rather than the hypothesized negative effect (Frenkel, 1976; Frankel, 1979). AbuDalu et al. (2008) obtains a similar result in an exchange rate model for Philippines. Bangladesh and the Philippines have both experienced some degree of economic instability and relatively high inflation at times in the recent past.

Table 7 indicates that the impact of the money supply differential on the exchange rate is 0.2, which implies that a 1% increase in the money supply of Bangladesh relative to the money supply of the United States results in depreciation of the taka relative to the dollar by 0.2%. That aligns with the basic monetary balance hypothesis. Evidence for other Asian economies also provide evidence in favor of that conjecture. A study of the Philippines (AbuDalu, 2008) documents that an increase in the money supply leads to depreciation of the peso.

The real output differential on the exchange rate is negative, which is consistent with the hypothesis. The coefficient of the real output differential is -0.34, which supports the conventional theory that an increase in relative real output will decrease relative inflation, holding other factors constant, and appreciate the domestic currency value. This outcome indicates that a 1% increase in relative real output will lead the domestic currency to appreciate by 0.34% against the dollar within one year.

As hypothesized, the sign for the error correction parameter (w_{t-1}) is less than zero. The value of the error coefficient is -0.54, which indicates 2 years are needed for any short-run departures from the equilibrium to dissipate. The t-statistic satisfies the 5% significance criterion. This is substantially faster than the 7-year adjustment period that Meerza (2012) documents for the taka.

Meerza (2012) considers the effects of both the money supply and international reserves in one model, whereas, in this analysis, those variables are considered in two separate models. The estimated model based on the balance of payments approach examines the effects of international reserves on the exchange rate and the model based on the monetary approach analyzes the effects of the money supply on the exchange rate. It is not surprising, then, that the estimated adjustment period documented by Meerza (2012) for a model combining characteristics of these two approaches (7 years) is in between the estimated adjustment periods derived from Tables 5 and 7 (11 years and 2 years respectively). The differences in the speed of adjustment between these two models may be partly attributable to the predictors included in those models. The exchange rate may respond more quickly to changes in the money supply than to changes in international reserves, which may account for the shorter adjustment period in the monetary model than in the balance of payments model. Moreover, the 2 years adjustment period reported in the monetary model estimates seems intuitively more plausible than the 11 years adjustment period suggested by the balance of payments model. However, the overall performance of the monetary model cannot be ascertained by examining only the error correction term. The model based on the balance of payments approach has more logical coefficient signs and magnitudes, overall, than model based on the monetary approach.

Table 7: Exchange rate error correction results based on the Monetary approach

Dependent Variable: d(s)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.007903	0.015590	0.506929	0.6162
d(s(-1))	0.537939	0.160027	3.361554	0.0023
d(p-p*)	-0.302083	0.087680	-3.445287	0.0018
d(p-p*(-1))	0.020785	0.091217	0.227861	0.8214
d(p-p*(-2))	0.170853	0.091070	1.876061	0.0711
d(r-r*)	0.003398	0.003733	0.910132	0.3705
d(m-m*)	0.195467	0.094326	2.072243	0.0476
d(y-y*)	-0.335159	0.282066	-1.188232	0.2447
W_{t-1}	-0.543508	0.126803	-4.286223	0.0002

Diagnostic statistics for the underlying ARDL model

R-squared	0.680860	Mean dependent var	0.044394
Adjusted R-squared	0.589677	S.D. dependent var	0.048342
S.E. of regression	0.030966	Akaike info criterion	-3.904063
Sum squared resid	0.026849	Schwarz criterion	-3.512218
Log likelihood	81.22517	Hannan-Quinn criter.	-3.765919
F-statistic	7.466981	Durbin-Watson stat	2.152590
Prob(F-statistic)	0.000027		

Chi-squared autocorrelation function Q-test for higher order autocorrelation

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	-0.077	-0.077	0.2347	0.628
		2	-0.064	-0.070	0.4025	0.818
		3	-0.023	-0.034	0.4258	0.935
		4	-0.144	-0.155	1.3338	0.856

According to the results obtained, bilateral taka exchange rate models based on the balance of payments approach appear to have better econometric and economic traits than equations based on the monetary constructs. The parameter estimates of equations based on the balance of

payments approach generally have more intuitive arithmetic signs than those associated with the monetary construct models. Moreover, the diagnostic statistics for the models based on the balance of payments approach appear superior to those for the models based on the monetary construct. In the next section, forecasts are generated to evaluate out-of-sample simulation accuracy for the balance of payments model. In addition to the relative sizes of ARDL and random walk forecast errors, the analysis includes evaluations of directional accuracy.

Chapter 5: Forecast Accuracy Analysis

Exchange rate forecasts are used in multiple planning efforts. Using the balance of payments specifications from above, Equation (20) describes long-run dynamics and Equation (21) describes short-run dynamics.

$$s_t = a_0 + a_1 (p - p^*)_t + a_2 (r - r^*)_t + a_3 IR_t + u_t \quad (20)$$

$$ds_t = b_0 + b_1 d(s_{t-1}) + b_2 d(p - p^*)_t + b_3 d(r - r^*)_t + b_4 d(IR_t) + b_5 d(IR_{t-1}) + b_6 u_{t-1} + v_t \quad (21)$$

Equation (22) results from solving Equation (20) for u_t and then substituting a one period lag of that expression into Equation (21). Equation (22) can be re-expressed as shown in Equation (23).

$$ds_t = b_0 + b_1 d(s_{t-1}) + b_2 d(p - p^*)_t + b_3 d(r - r^*)_t + b_4 d(IR_t) + b_5 d(IR_{t-1}) + b_6 (s_{t-1} - a_0 - a_1 (p - p^*)_{t-1} - a_2 (r - r^*)_{t-1} - a_3 IR_{t-1}) + v_t \quad (22)$$

$$ds_t = b_0 - b_6 a_0 + b_1 d(s_{t-1}) + b_6 (s_{t-1}) + b_2 d(p - p^*)_t + b_3 d(r - r^*)_t + b_4 d(IR_t) + b_5 d(IR_{t-1}) - b_6 a_1 (p - p^*)_{t-1} - b_6 a_2 (r - r^*)_{t-1} - b_6 a_3 (IR_{t-1}) + v_t \quad (23)$$

An expression describing the evolution of the exchange rate in level, rather than first-differenced, form is obtained by substituting Equation (23) into the formula $s_t = s_{t-1} + ds_t$ and rearranging terms as shown in Equation (24).

$$s_t = s_{t-1} + b_0 - b_6 a_0 + b_1 d(s_{t-1}) + b_6 (s_{t-1}) + b_2 d(p - p^*)_t + b_3 d(r - r^*)_t + b_4 d(IR_t) + b_5 d(IR_{t-1}) - b_6 a_1 (p - p^*)_{t-1} - b_6 a_2 (r - r^*)_{t-1} - b_6 a_3 (IR_{t-1}) + v_t$$

$$= b_0 - b_6 a_0 + b_1 d(s_{t-1}) + s_{t-1} (1 + b_6) + b_2 d(p - p^*)_t + b_3 d(r - r^*)_t + b_4 d(IR_t) + b_5 d(IR_{t-1}) - b_6 a_1 (p - p^*)_{t-1} - b_6 a_2 (r - r^*)_{t-1} - b_6 a_3 (IR_{t-1}) + v_t \quad (24)$$

Equation (24) can be expressed for simulation purposes as shown in Equation (25).

$$s_t = \mu_0 + \mu_1 s_{t-1} + \mu_2 d(s_{t-1}) + \mu_3 d(p - p^*)_t + \mu_4 d(r - r^*)_t + \mu_5 d(IR_t) + \mu_6 d(IR_{t-1}) - \mu_7 (p - p^*)_{t-1} - \mu_8 (r - r^*)_{t-1} - \mu_9 (IR_{t-1}) + v_t \quad (25)$$

An expanding re-estimation and simulation procedure is employed to produce multiple sets of exchange rate forecasts for the years 2007 to 2015. The dataset used for estimation purposes begins in 1976. In order to provide an adequate number of observations for statistical analysis of forecast accuracy, multiple sets of forecasts are generated from that dataset. In the first step, the models are estimated using data from 1976 to 2006 and the three-year ahead forecast period runs from 2007 to 2009. Subsequently, the estimation period is extended by one year and the forecast period covers 2008 to 2010. This process is repeated multiple times until the forecast period runs from 2013 to 2015. Random walk and random walk with drift forecasts are also generated and used as benchmarks. Root Mean Squared Error (RMSE) and Theil inequality coefficient (also known as a U-statistic) statistics measure how well the forecasted values of the taka/ dollar exchange rate track the actual currency values. When the RMSE and U-statistics equal zero, that indicates perfect forecast precision. The range of RMSE is between 0 to ∞ and the range of the U-statistic is 0 to 1 (Pindyck and Rubinfeld, 1998).

The second moment of the U-statistics can be broken down into three components (Pindyck and Rubinfeld, 1998). The first component, U-Mean, indicates the amount of forecast error due to bias. The second component is U-Var, which indicates the degree to which the forecast replicates the actual observed variance of the series. The third component, U-Covar, indicates the prediction error due to unsystematic error. The sum of these components is one and, if U≠ 0, then a high value for U-Covar and low values for U-Mean and U-Var indicate good forecasting performance. These statistics are calculated as shown in Equation (26):

$$U = \frac{\sqrt{\frac{1}{n}\sum(F_t - A_t)^2}}{\sqrt{\frac{1}{n}\sum F_t^2} + \sqrt{\frac{1}{n}\sum A_t^2}} \qquad (26)$$

U-Mean = $\frac{(\bar{F} - \bar{A})^2}{\frac{1}{n}\sum(F_t - A_t)^2}$

U-Var = $\frac{(\sigma_F - \sigma_A)^2}{\frac{1}{n}\sum(F_t - A_t)^2}$

U-Covar = $\frac{2(1-r)\sigma_F\sigma_A}{\frac{1}{n}\sum(F_t - A_t)^2}$

In Equation (26), F_t and A_t are the forecasted and actual values at time t, $\bar{F}$, $\bar{A}$ and σ_F, σ_A are the means and standard deviations of F and A, respectively, and r is the correlation coefficient for F and A.

Table 8 through Table 11 examine out-of-sample prediction accuracy of the random walk benchmarks and the ARDL model based on the balance of payments approach. The most accurate forecasts are shown in bold. The estimated results in Table 8 represent the performance of the model as measured by RMSE and Theil U-statistics. Prediction errors are used to calculate the RMSE, U-Statistics, and second moment error proportions for bias (U-Mean), variance (U-Var), and covariance (U-Covar). According to Table 8, the Theil U-statistics indicate that the ARDL forecasts based on the balance of payments approach (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. All three sets of forecasts analyzed in Table 8 are found to be unbiased. The out-of-sample simulation errors for all three methods are also found to be random in nature.

Table 8. RMSE and Theil Inequality Statistics

	ARDL	RW	RWD
RMSE	0.1794054388	**0.047912026**	0.063688765
U-Stat	0.02086185	0.005588156	**0.007407569**
U-Mean	0.027280749	0.133986141	**0.007694891**
U-Var	0.212139511	**0.002020884**	0.276911747
U-Covar	0.7834850043	**0.863992975**	0.715393361
Number of forecast obsvns.	21	21	21

The information provided in Table 8 is useful, but descriptive, only. Another way to compare forecasting performance is through statistical hypothesis tests such as the Diebold-Mariano Test. According to Diebold and Mariano (1995), the forecast error differential can be defined as $d_t = MSE(e_{RWt}) - MSE(e_{ARDLt})$, where $MSE(e_{RWt})$ and $MSE(e_{ARDLt})$ are mean squared error statistics for the RW and ARDL forecasts, respectively. The null hypothesis is that both sets of forecasts are equally accurate, which is equivalent to the hypothesis that the population mean of the differential variable is equal to zero as shown in Equation (27).

$$H_0: \mu(d) = 0 \qquad (27)$$

The Diebold and Mariano (DM) statistic is expressed in Equation (28), where $\bar{d}$ is the sample mean of d_t and $\hat{V}(\bar{d})$ is the variance of $\bar{d}$.

$$DM = \frac{\bar{d}}{\sqrt{\hat{V}(\bar{d})}} \qquad (28)$$

A positive value of the DM statistic implies that the ARDL forecasts are more accurate than the random walk benchmarks. A one-tailed test with critical values from a normal distribution can be used to determine whether the difference in accuracy is statistically significant (Kilian and

Taylor, 2003). According to Table 9, RW and RWD benchmarks provide significantly more accurate forecasts than the ARDL model, which is based on the balance of payments approach. Therefore, the null hypothesis, H_0, that both sets of forecast are equally accurate, can be rejected. Furthermore, the RW forecasts are not significantly better than the RWD forecasts. Berkowitz and Giorgianni (2001) find that, according to the Diebold-Mariano test, the US dollar exchange rate forecasts for the Canadian dollar, German Mark, Japanese Yen and Swiss France models have roughly the same degree of accuracy as the RW benchmark used in that study. In the case of the US dollar/Canadian dollar and US dollar/German Mark exchange rates, the random walk is somewhat more accurate than the econometric model over most time horizons considered. In the other two cases, the econometric model is somewhat more accurate than the random walk.

Table 9: Diebold-Mariano Test Results

Test		DM statistics	Decision
Diebold Mariano	ARDL Vs RW	-7.451	**Reject (0.0000)**
	ARDL Vs RWD	-6.351	**Reject (0.0000)**
	RWD Vs RW	-1.083	**Fail to Reject (0.2787)**
Number of Observations	21		

**Significant at 1%
* Significant at 5%

The relative accuracy of competing forecasts can be further assessed through an error differential regression test. The exact form of the test is determined by the signs of the means of the prediction errors (Ashley, Granger, and Schmalensee, 1980). The purpose of this test is to establish whether the ARDL model mean squared error (MSE) is statistically different from the RW MSE and RW with drift MSE. The procedure tests the null hypothesis shown in Equation (29):

$$H_o: \text{MSE}(e_1) = \text{MSE}(e_2) \quad (29)$$

where MSE is the mean squared error and e_1 and e_2 are the forecast errors for two competing sets of forecasts.

In this study, MSE (e_1) represents the mean squared error for the ARDL forecasts, and MSE (e_2) represents the mean squared error for the random walk or the random walk with drift forecasts. Using the expression shown in Equation (29),

$$\Delta_t = e_{ARDLt} - e_{RWt} \text{ and } \Sigma_t = e_{ARDLt} + e_{RWt} \qquad (30)$$

Equation (30) can be rewritten:

$$MSE(e_{ARDL}) - MSE\ (e_{RW}) = [\mu\ (e_{ARDL})^2 - \mu\ (e_{RW})^2] + cov\ (\Delta, \Sigma) = 0 \qquad (31)$$

In Equation (31), cov stands for covariance and μ denotes the mean of the forecast errors. Forecast errors are judged to be statistically different if it is possible to reject the joint null hypothesis that $\mu(\Delta) = 0$ and $cov(\Delta, \Sigma) = 0$. That null hypothesis is tested using a regression equation as shown in Equations (32) and (33).

Equation (32) is the specification for testing the null hypothesis when the error means have the same sign and Equation (33) is employed when the error means have opposite signs.

$$\Delta_t = \beta_1 + \beta_2\ [\ \Sigma_t - m\ (\Sigma_t)] + u_t \qquad (32)$$

$$\Sigma_t = \beta_1 + \beta_2\ [\ \Delta_t - m\ (\Delta_t)] + u_t \qquad (33)$$

In Equation (32) and Equation (33), u_t is a randomly distributed error term and the signs of β_1 and β_2 indicate which set of forecasts is more accurate.

The mean error values of the three sets of forecasts shown in Table 11 have different signs and that affects the interpretation of these results. In this study, the forecast error means are -0.012 for the ARDL model, -0.0175 for the RW, and 0.006 for the RWD. Furthermore, conclusions regarding the relative accuracy of competing sets of forecasts depend on the signs of the regression parameters β_1 and β_2 obtained by estimating Equations (32) and (33). For the ARDL vs. RW comparison both estimated coefficients are positive, while the estimated coefficients for the RW vs. RWD comparison are both negative and those for the ARDL vs. RWD comparison are of

opposite signs, with β_1 negative and β_2 positive. Decision rules for determining whether to reject the null hypothesis based on t-statistics and F-statistics are given in Ashley, Granger, and Schmalensee (1980), which is given in Table 10.1 and Table 10.2. Table 10.2 was used for testing the null hypothesis in all three comparisons.

Table 10.1: Decision rules for error differential regression test:

Model error mean is positive		$b_1 > 0$		$b_1 < 0$	
		b_1 significant	b_1 insignificant	b_1 significant	b_1 insignificant
$b_2 > 0$	b_2 significant	REJECT	REJECT	-	REJECT
	b_2 insignificant	REJECT	-	-	-
$b_2 < 0$	b_2 significant	-	-	-	-
	b_2 insignificant	REJECT	-	-	-

Table 10.2:

Model error mean is negative		$b_1 > 0$		$b_1 < 0$	
		b_1 significant	b_1 insignificant	b_1 significant	b_1 insignificant
$b_2 > 0$	b_2 significant	-	REJECT	REJECT	REJECT
	b_2 insignificant	-	-	REJECT	-
$b_2 < 0$	b_2 significant	-	-	-	-
	b_2 insignificant	-	-	REJECT	-

Table 11 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, Granger, and Schmalensee, 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 $\beta_1 = \beta_2 = 0$. According to Ashley, Granger and Schmalensee (1980), the true significance level associated with this F-statistic is never more than half the probability obtained from tables of the F distribution. In the RW vs. RWD comparison, the sign of β_1 is consistent with RWD superiority (although the coefficient is

statistically insignificant) but 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, Granger, and Schmalensee, 1980).

Table 11 summarizes the error differential regression test results. According to the results of a one-tailed t-test, the RW predictions are relatively more accurate than the ARDL model forecasts. In the second row, the value of the F-statistic is statistically significant, which indicates that RWD predictions are relatively more accurate than the ARDL model forecasts. For the RW vs. RWD comparison, the calculated t-statistic for β_2 is 2.297 and the associated probability value for a one-tailed t-test is 0.0000, while β_1 is statistically insignificant. This indicates that it is not possible to reject the null hypothesis that the RWD forecasts are no more accurate than the RW forecasts. These results are similar to those documented in Meese and Rogoff (1983) where the estimated model fails to outperform the random walk in out-of-sample simulations.

Table 11: Error Differential Regression Test Results

Test		F-Stat	
Error differential regression	ARDL Vs RW	42.64 **	**Reject**
	ARDL Vs RWD	14.57**	**Reject**
	RW Vs RWD	2.297 **	**Do not Reject**
Number of Observations	21		

**Significant at 1%
* Significant at 5%

Error Differential Regression Test Results ARDL Vs RW:

Dependent Variable: DEP
Method: Least Squares
Date: 05/25/17 Time: 09:44
Sample: 2001 2021
Included observations: 21

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.005671	0.016022	0.353933	0.7273
IND	0.727244	0.078808	9.228076	0.0000

R-squared	0.817584	Mean dependent var	0.005671
Adjusted R-squared	0.807983	S.D. dependent var	0.167550
S.E. of regression	0.073420	Akaike info criterion	-2.294845
Sum squared resid	0.102420	Schwarz criterion	-2.195367
Log likelihood	26.09587	Hannan-Quinn criter.	-2.273256
F-statistic	85.15739	Durbin-Watson stat	2.521890
Prob(F-statistic)	0.000000		

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability

F-statistic	42.64133	(2, 19)	0.0000
Chi-square	85.28266	2	0.0000

Null Hypothesis: C(1)=C(2)=0
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(1)	0.005671	0.016022
C(2)	0.727244	0.078808

Restrictions are linear in coefficients.

Error Differential Regression Test Results ARDL Vs RWD:

Dependent Variable: DEP
Method: Least Squares
Date: 05/25/17 Time: 01:30
Sample: 2001 2021
Included observations: 21

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.006280	0.028037	-0.224005	0.8251
IND	0.815835	0.151284	5.392729	0.0000

R-squared	0.604838	Mean dependent var	-0.006280
Adjusted R-squared	0.584040	S.D. dependent var	0.199211
S.E. of regression	0.128481	Akaike info criterion	-1.175675
Sum squared resid	0.313641	Schwarz criterion	-1.076197
Log likelihood	14.34459	Hannan-Quinn criter.	-1.154086
F-statistic	29.08152	Durbin-Watson stat	2.362875
Prob(F-statistic)	0.000033		

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
F-statistic	14.56585	(2, 19)	0.0001
Chi-square	29.13170	2	0.0000

Null Hypothesis: C(1)=C(2)=0
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.

C(1)	-0.006280	0.028037
C(2)	0.815835	0.151284

Restrictions are linear in coefficients.

Error Differential Regression Test Results RWD Vs RW

Dependent Variable: DEP
Method: Least Squares
Date: 06/15/17 Time: 16:56
Sample: 2001 2021
Included observations: 21

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.011951	0.020441	-0.584646	0.5657
IND	-1.082554	0.471230	-2.297295	0.0331

R-squared	0.217384	Mean dependent var	-0.011951
Adjusted R-squared	0.176194	S.D. dependent var	0.103206
S.E. of regression	0.093674	Akaike info criterion	-1.807598
Sum squared resid	0.166722	Schwarz criterion	-1.708120
Log likelihood	20.97978	Hannan-Quinn criter.	-1.786009
F-statistic	5.277564	Durbin-Watson stat	1.916042
Prob(F-statistic)	0.033136		

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
F-statistic	2.809688	(2, 19)	0.0853
Chi-square	5.619375	2	0.0602

Null Hypothesis: C(1)=C(2)=0
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(1)	-0.011951	0.020441
C(2)	-1.082554	0.471230

Restrictions are linear in coefficients.

In addition to forecast accuracy, directional forecast evaluations are also completed. Pesaran and Timmermann (1994) propose a test where the null hypothesis tested is that the actual directional changes and those predicted by the ARDL model are independently distributed. The test involves calculating two new variables. The first variable, $\widehat{\mathrm{P}}$, is the proportion of times that the direction of change is correctly forecasted and the second variable, $\widehat{P}_*$, is the proportion of correct predictions that would be expected if the forecasted directional changes were distributed independently of the actual observed directional changes. The variance of these two variables must be computed to construct the test statistic shown in Equation (34).

If the computed Pesaran-Timmermann (PT) statistic is higher than the 5% critical value for a one-sided normal test, then the null hypothesis can be rejected, which implies that the forecasts provide useful information on the direction of change (Granger and Pesaran, 2000). According to the Table 12, the PT statistic is lower than the 5% critical value for a one-sided normal test and the null hypothesis cannot be rejected. Therefore, the forecasts fail to provide useful information on the direction of change at the 5% level of significance.

Table 12: Directional Accuracy for ARDL Model

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

Overall, the ARDL model falls short of the RW and RW with drift models in terms of forecasting performance. Moreover, the directional accuracy statistics indicate that the ARDL forecasts fail to provide useful information on the direction of change of the exchange rate at the

5% level of significance. Further research employing different sample data sets is required in order to confirm these results.

While the forecasting performance of the ARDL model falls short of expectations, the diagnostic statistics in Tables 4 and 5 suggest that the model does capture a number of critical factors affecting the taka / dollar exchange rate. The parameter estimates from the model could be used to simulate the effects on the exchange rate 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 nation's foreign reserves (Maurer et al., 2017). The ARDL model could be used to simulate the short- and long-run repercussions of this incident in terms of 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.

Chapter 6: Conclusion

In this study, ARDL models based on balance of payments and monetary approaches are estimated to study long-term and short-term taka / dollar exchange rate dynamics in Bangladesh. Prior to estimating the models, Augmented Dickey-Fuller unit root tests are carried out and indicate that all the variables included in the two models are either I(0) or I(1). Accordingly, the data are suitable for analysis within the ARDL framework. The bounds tests confirm that the variables of the models are cointegrated.

The bilateral taka / dollar exchange rate model based on the balance of payments approach has better econometric and statistical traits than the model based on the monetary constructs. Overall, the effect of inflation on the exchange rate is manifested primarily in the long-run rather than the short-run. The exchange rate model based on the balance of payments approach indicates that an increase in inflation results in depreciation of the domestic currency in the long-run. Conversely, increments in the interest rate and international reserves cause the taka to appreciate in both the long-run and short-run.

The study also examines the accuracy of exchange rate forecasts generated with the balance of payments model using Theil U-statistics, non-parametric tests, and error differential regression tests. Furthermore, directional forecast evaluations determine the ability of the model to accurately predict the direction of change in the exchange rate. Random walk and random walk with drift benchmarks are used to evaluate predictive accuracy.

Theil U-statistics indicate that the random walk benchmarks are more accurate overall. The balance of payments forecasts have higher U-statistics than both of the random walk benchmarks. Moreover, the results for the non-parametric test and for the error differential regression technique also point to the superiority of random walk benchmarks. According to the Pesaran-Timmerman

test, the actual and the predicted directional changes are independently distributed. That implies that the ARDL balance of payments model forecasts fail to provide useful information on the direction of change.

The low predictive power of the balance of payments ARDL model may partially be a consequence of the limited number of observations available in the sample. As new data become available, more testing can be completed. For future research, quarterly or monthly data can also be used for analyzing exchange rate behavior in Bangladesh. The results obtained herein indicate that inflation, interest rates, and international reserves affect taka / dollar exchange rate dynamics in Bangladesh. Predicting future changes in this bilateral exchange rate does not appear very feasible.

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Appendix

Table A.1: ARDL Analysis of Exchange Rate Results using Balance of Payments Approach

Long Run Coefficients for ARDL(1, 1, 1, 1) model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
c	8.527976	3.008360	2.834341	0.0080
p - p*	2.412840	0.922346	2.615983	0.0136
r - r*	-0.070774	0.046532	-1.520969	0.1384
IR	-0.482142	0.333435	-1.445987	0.1582

Diagnostic statistics for the underlying ARDL model

R-squared	0.996511	Mean dependent var	3.714850
Adjusted R-squared	0.995724	S.D. dependent var	0.515636
S.E. of regression	0.033720	Akaike info criterion	-3.760785
Sum squared resid	0.035248	Schwarz criterion	-3.419542
Log likelihood	81.33531	Hannan-Quinn criter.	-3.638350
F-statistic	1264.989	Durbin-Watson stat	1.523816
Prob(F-statistic)	0.000000		

*Note: p-values and any subsequent tests do not account for model

selection.

Exchange Rate Error Correction Results based on Balance of Payments Approach

Dependent Variable: d(s)

Short Run Coefficients for ARDL(1, 1, 1, 1) model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
c	-1.74E-05	0.010316	-0.001686	0.9987
d(p - p*)	-0.082968	0.072433	-1.145451	0.2600
d(r - r*)	-5.85E-05	0.003564	-0.016410	0.9870
d(IR)	-0.006059	0.014679	-0.412757	0.6824
u_{t-1}	-0.085588	0.015062	-5.682530	0.0000

Diagnostic statistics for the underlying ARDL model

R-squared	0.679121	Mean dependent var	0.042602
Adjusted R-squared	0.617015	S.D. dependent var	0.048947
S.E. of regression	0.030291	Akaike info criterion	-3.991110
Sum squared resid	0.028444	Schwarz criterion	-3.689450
Log likelihood	82.83110	Hannan-Quinn criter.	-3.883782
F-statistic	10.93493	Durbin-Watson stat	1.721133
Prob(F-statistic)	0.000002		

Table A.2: ARDL Analysis of Exchange Rate Results using Balance of Payments Approach

Long Run Coefficients for ARDL(2, 1, 0, 2) model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
c	6.219976	1.856375	3.350604	0.0023
p - p*	1.683982	0.617939	2.725157	0.0108
r - r*	-0.040923	0.030371	-1.347438	0.1884
IR	-0.216184	0.210234	-1.027813	0.3125

Diagnostic statistics for the underlying ARDL model

R-squared	0.996930	Mean dependent var	3.740686
Adjusted R-squared	0.996083	S.D. dependent var	0.496316
S.E. of regression	0.031063	Akaike info criterion	-3.902212
Sum squared resid	0.027982	Schwarz criterion	-3.514362
Log likelihood	83.14202	Hannan-Quinn criter.	-3.764218
F-statistic	1177.091	Durbin-Watson stat	1.762757
Prob(F-statistic)	0.000000		

Exchange rate error correction results based on Balance of Payments Approach

Short Run Coefficients for ARDL(2, 1, 0, 2) model

Dependent variable: d(s)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000571	0.014079	0.040573	0.9679
D(S(-1))	0.280101	0.130200	2.151312	0.0394
D(DIFP)	-0.124439	0.072506	-1.716253	0.0961
D(DIFR)	-0.002155	0.003433	-0.627841	0.5347
D(IR)	-0.012415	0.015899	-0.780844	0.4408
D(IR(-1))	-0.043294	0.015338	-2.822703	0.0082
U1(-1)	-0.095464	0.026827	-3.558532	0.0012

Diagnostic statistics for the underlying ARDL model

R-squared	0.687361	Mean dependent var	0.042602
Adjusted R-squared	0.626850	S.D. dependent var	0.048947
S.E. of regression	0.029900	Akaike info criterion	-4.017125
Sum squared resid	0.027713	Schwarz criterion	-3.715464
Log likelihood	83.32537	Hannan-Quinn criter.	-3.909796
F-statistic	11.35930	Durbin-Watson stat	1.758612
Prob(F-statistic)	0.000001		

Table A.3: ARDL Analysis of Exchange Rate Results using the Monetary Construct

Selected Model: ARDL(1, 1, 1, 0, 0)

Long Run Coefficients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
c	3.981875	0.430973	9.239259	0.0000
p - p*	1.002025	0.188917	5.304049	0.0000
r - r*	-0.023099	0.019887	-1.161517	0.2543
m - m*	0.028693	0.012785	2.244280	0.0321
y - y*	0.171830	0.356591	0.481870	0.6333

Diagnostic statistics for the underlying ARDL model

R-squared	0.995630	Mean dependent var	3.714850
Adjusted R-squared	0.994643	S.D. dependent var	0.515636
S.E. of regression	0.037741	Akaike info criterion	-3.535477
Sum squared resid	0.044155	Schwarz criterion	-3.194234
Log likelihood	76.94181	Hannan-Quinn criter.	-3.413042
F-statistic	1008.910	Durbin-Watson stat	1.432797
Prob(F-statistic)	0.000000		

*Note: p-values and any subsequent tests do not account for model selection.

Exchange rate error correction results based on Monetary Construct

Dependent variable: d(s)
Short Run Coefficients for ARDL(1, 1, 1, 0, 0) model

Cointegrating Form

Variable	Coefficient	Std. Error	t-Statistic	Prob.
c	0.005293	0.014025	0.377393	0.7083
d(p - p*)	-0.113576	0.079500	-1.428628	0.1625
d(r - r*)	0.005855	0.003730	1.569663	0.1260
d(m - m*)	0.006701	0.002613	2.564802	0.0151
d(y - y*)	-0.014071	0.264314	-0.053238	0.9579
w_{t-1}	-0.152746	0.039633	-3.854055	0.0005

Diagnostic statistics for the underlying ARDL model

R-squared	0.512933	Mean dependent var	0.041477
Adjusted R-squared	0.439135	S.D. dependent var	0.048807
S.E. of regression	0.036552	Akaike info criterion	-3.639512
Sum squared resid	0.044090	Schwarz criterion	-3.383580
Log likelihood	76.97049	Hannan-Quinn criter.	-3.547686
F-statistic	6.950486	Durbin-Watson stat	1.440442
Prob(F-statistic)	0.000157		

Table A.4**:** ARDL Analysis of Exchange Rate Results using Monetary Constructs

Long Run Coefficients for ARDL(2, 1, 2, 2, 0) model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
c	4.556333	0.573557	7.943987	0.0000
p - p*	0.605391	0.265829	2.277369	0.0312
r - r*	-0.008932	0.019734	-0.452631	0.6546
m - m*	0.040235	0.016903	2.380309	0.0249
y - y*	0.888095	0.431096	2.060089	0.0495

Diagnostic statistics for the underlying ARDL model

R-squared	0.996601	Mean dependent var	3.740686
Adjusted R-squared	0.995663	S.D. dependent var	0.496316
S.E. of regression	0.032685	Akaike info criterion	-3.800392
Sum squared resid	0.030981	Schwarz criterion	-3.412543
Log likelihood	81.20745	Hannan-Quinn criter.	-3.662398
F-statistic	1062.789	Durbin-Watson stat	2.155401
Prob(F-statistic)	0.000000		

*Note: p-values and any subsequent tests do not account for model selection.

Exchange rate error correction results based on Monetary Construct

Dependent variable: d(s)

Short Run Coefficients for ARDL(2, 1, 2, 2, 0) model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
c	0.000520	0.013585	0.038305	0.9697
d(s (-1))	0.533907	0.141523	3.772579	0.0007
d(p – p*)	-0.287205	0.074026	-3.879782	0.0006
d(r – r*)	0.003650	0.003636	1.003861	0.3237
d(r (-1) – r* (-1))	-0.007498	0.003127	-2.397515	0.0232
d(m - m*)	0.010127	0.002278	4.445802	0.0001
d(m (-1) – m* (-1))	-0.004447	0.002419	-1.838430	0.0763
d(y – y*)	0.126413	0.279992	0.451489	0.6550
w_{t-1}	-0.158386	0.033699	-4.700070	0.0001

Diagnostic statistics for the underlying ARDL model

R-squared	0.664255	Mean dependent var	0.042602
Adjusted R-squared	0.599272	S.D. dependent var	0.048947
S.E. of regression	0.030985	Akaike info criterion	-3.945822
Sum squared resid	0.029762	Schwarz criterion	-3.644161
Log likelihood	81.97061	Hannan-Quinn criter.	-3.838493
F-statistic	10.22198	Durbin-Watson stat	2.138263
Prob(F-statistic)	0.000003		

Historical Data

Year	Nominal Exchange Rate taka / $	Bangladesh GDP implicit price deflator, 2005 = 100	USA GDP implicit price deflator, 2005 = 100	Bangladesh 3-6 month scheduled bank fixed deposit rate, %	United States 3-month Certificate of Deposit rate, %
1976	15.40	10.209	35.965	6.75	5.27
1977	15.38	9.878	38.196	7.00	5.64
1978	15.02	12.884	40.877	7.00	8.22
1979	15.55	14.549	44.251	7.00	11.23
1980	15.45	23.331	48.242	8.25	13.07
1981	17.99	25.071	52.748	12.00	15.91
1982	22.12	27.923	56.019	12.00	12.27
1983	24.62	30.419	58.230	12.00	9.07
1984	25.35	35.011	60.297	12.00	10.37
1985	27.99	38.728	62.226	12.00	8.05
1986	30.41	41.634	63.482	12.00	6.52
1987	30.95	45.965	65.101	12.00	6.86
1988	31.73	49.107	67.380	12.00	7.73
1989	32.27	53.329	70.000	12.00	9.09
1990	34.57	56.343	72.590	12.04	8.15
1991	36.60	60.060	75.005	12.05	5.84
1992	38.95	61.847	76.715	10.47	3.68
1993	39.57	62.025	78.541	8.18	3.17
1994	40.21	64.364	80.213	6.40	4.63
1995	40.28	69.092	81.885	6.04	5.92
1996	41.79	72.018	83.380	7.28	5.39
1997	43.89	74.243	84.807	8.11	5.62
1998	46.91	78.159	85.728	9.30	5.47
1999	49.09	81.798	87.039	9.44	5.33
2000	52.14	83.317	89.020	8.69	6.46
2001	55.81	84.640	91.049	9.15	3.69
2002	57.89	87.344	92.446	7.91	1.73
2003	58.15	91.299	94.290	7.11	1.15
2004	59.51	95.170	96.882	5.80	1.56
2005	64.33	100.000	100.000	5.53	3.51
2006	68.93	122.023	103.072	5.99	5.15

2007	68.87	129.920	105.815	6.99	5.27
2008	68.60	140.133	107.891	7.55	2.97
2009	69.04	149.612	108.710	7.81	0.56
2010	69.65	160.301	110.038	7.21	0.31
2011	74.15	171.555	112.309	8.84	0.18
2012	81.86	185.615	114.379	10.22	0.12
2013	78.10	198.697	116.244	11.72	0.08
2014	77.63	211.698	118.153	9.80	0.08
2015	77.63	222.701	119.337	8.24	0.08

Year	Bangladesh liquid International Reserves (US$, billions)	Bangladesh M2 money supply (Thousands of Taka)	USA M2 money supply (Billions of US$)	Bangladesh Nominal GDP (Billions of national currency, Taka)
1976	0.288920	17,000,000	1,153.50	107.4600
1977	0.232670	21,000,000	1,273.00	105.3600
1978	0.315230	27,000,000	1,370.80	146.3700
1979	0.386250	33,000,000	1,479.00	172.8200
1980	0.299650	40,000,000	1,604.80	280.7800
1981	0.138420	47,000,000	1,760.30	322.1400
1982	0.182620	52,000,000	1,917.20	361.7400
1983	0.524080	73,000,000	2,136.20	408.3100
1984	0.389910	100,000,000	2,320.90	489.7900
1985	0.336520	110,000,000	2,506.60	561.9400
1986	0.409090	130,000,000	2,744.30	632.6900
1987	0.843150	160,000,000	2,842.90	727.7100
1988	1.046060	180,000,000	3,006.30	799.9300
1989	0.501460	210,000,000	3,171.40	890.6000
1990	0.628650	230,000,000	3,289.60	1,003.2900
1991	1.278240	270,000,000	3,390.50	1,105.1800
1992	1.824600	300,000,000	3,445.40	1,195.4200
1993	2.410810	330,000,000	3,499.90	1,253.7000
1994	3.138700	390,000,000	3,514.90	1,354.1200
1995	2.339670	440,000,000	3,661.00	1,525.1800
1996	1.834620	490,000,000	3,837.60	1,663.2400
1997	1.581460	530,000,000	4,052.70	1,807.0100
1998	1.905410	600,000,000	4,395.50	2,001.7700
1999	1.603640	687,394,000	4,660.00	2,196.9700
2000	1.485960	820,000,000	4,945.50	2,370.8600
2001	1.275030	1,200,000,000	5,466.80	2,535.4600
2002	1.683210	1,300,000,000	5,808.30	2,732.0100
2003	2.577890	1,500,000,000	6,093.60	3,005.8000
2004	3.172440	1,700,000,000	6,436.70	3,329.7300
2005	2.767240	2,000,000,000	6,698.20	3,707.0700
2006	3.805600	2,400,000,000	7,094.20	4,823.3700
2007	5.183430	2,800,000,000	7,521.80	5,498.0000

2008	5.689280	3,200,000,000	8,269.20	6,286.8200
2009	10.218900	3,900,000,000	8,552.30	7,050.7200
2010	10.564300	4,700,000,000	8,848.90	7,975.3900
2011	8.509530	5,500,000,000	9,692.30	9,087.0500
2012	12.031200	6,400,000,000	10,490.90	10,473.0000
2013	17.564340	6,539,666,000	11,068.50	11,885.3000
2014	21.785400	7,412,483,000	11,718.70	13,430.5000
2015	27.023380	8,381,142,000	12,401.50	15,054.3000

Vita

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