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Exchange Rate Determination of Bangladesh: A Cointegration Approach

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In this paper, I propose and estimate a model to determine the exchange rate for the Bangladeshi Taka (BDT) vis-à-vis. US Dollar (USD). I use monthly data for the period of January 1999 to August 2008. I employ the Johansen cointegration technique and I find that nominal exchange rate is cointegrated with several macroeconomic variables. As such, the model is consistent with standard international economic theory. In addition, I find that this model provides out-of-sample forecasts that are better than naïve random walk forecasting model. That is, the information that the cointegrated relationship provides, improves forecasting performance.

1. Introduction

In the current flexible-exchange-rate environment, exchange rate determination is an important concern of policy makers. The exchange rate is one major factor that determines a country's balance of trade. Because Bangladesh follows an export-oriented growth policy, it depends heavily on international trade. A sound knowledge about the trend of exchange rate fluctuations would be helpful to identify investment opportunities.

According to Meese and Rogoff (1983) exchange rate models fail to beat the performance in terms of out-of-sample forecasts of naïve random walk model. After that researchers start to compare the performance of fundamental based structural exchange rate model with other models in case of out-of-sample forecasts. Many recent literatures such as MacDonald and Taylor (1993), Karfakis (2006) and Korap

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(2008) show the superiority of fundamental based models as compared to random walk forecasting model. In their research papers, they show the out-of-sample forecasting performance of fundamental based model is better than random walk models.

Determining the exchange rate for a least developed country such as Bangladesh is important because it allows economists to investigate international financial theories and it also allows policy makers in this case to learn about *ex ante* policy and efficient forecasting techniques. Until now there is no literature that models Bangladesh's exchange rate. For this reason, this paper contributes significantly in this field.
The two objectives of this paper are to model the relationship between the nominal exchange rate and macroeconomic variables suggested by economic theory and to compare out-of-sample forecasting performance of this model against a naïve random walk forecasting model. This paper is organized as follows. Section 2 specifies the model. Section 3 identifies the data and section 4 reports results. The forecasting performance of estimated model is discussed in section 5. The last section offers conclusion.

2. The model

To begin, I specify the theory of Purchasing Power Parity (PPP) as:

$$S = P_{BD}/P_{US} \tag{1}$$

where, S denotes number of BDT per US dollar; P_{BD} the price level of Bangladesh and P_{US} the US price level.

The quantity theory of money for Bangladesh is $M_{BD} \cdot V_{BD} = P_{BD} \cdot Y_{BD}$ and for US, it is $M_{US} \cdot V_{US} = P_{US} \cdot Y_{US}$. Solving simultaneously by eliminating the ratios of price levels yield equation 2:

$$S = [(M_{BD}/M_{US}) \cdot (V_{BD}/V_{US})] / (Y_{US}/Y_{BD}) \tag{2}$$

where, M_{BD}/M_{US} = relative money supply V_{BD}/V_{US} = relative velocity of money Y_{US}/Y_{BD} = relative income

Taking natural log of equation 2 and I get equation 3,

$$logS = (log\ M_{BD} - logM_{US}) - (logY_{BD} - logY_{US}) + (logV_{BD} - logV_{US}) \quad (3)$$

I assume that the interest and inflation rates largely determine the velocity of money for both countries. Thus, int_{BD} and inf_{BD} denote interest and inflation rates respectively for Bangladesh. On the other hand, int_{US} and inf_{US} indicate interest rate and inflation rate for US respectively. Therefore, I specify equation 3 as equation 4, which I later estimate.

$$ex_t = \beta_1 + \beta_2 M1_t + \beta_3 ipi_t + \beta_4 int_t + \beta_5 inf_t + \varepsilon_t \quad (4)$$

where, $ex = logS$

$M1 = log\ M_{BD} - logM_{US}$

$ipi = logY_{BD} - logY_{US}$

$int = log\ int_{BD} - log\ int_{US}$

$inf = log\ inf_{BD} - log\ inf_{US}$

$\varepsilon = error\ term$

Oskooee and Kara (2000) also use the same model to test the exchange rate overshooting hypothesis in the short run as well as in the long run for Turkey.

3. Data specification

I collect all data from International Financial Statistics which the International Monetary Fund publishes. I use monthly data for the period of January 1999 to August 2008. I select this time period because monthly data for industrial production index of Bangladesh after August, 2008 is not available.

Table 1: Expected sign of variables

	Variable	Expected sign	Proxy	Data source	Time period
Dependent variable	ex $(logS)$	…	Exchange rate (BDT per USD)	IFS of IMF	1999:01 to 2008:08
Independent variables	M1 $(logM1_{BD} - logM1_{US})$	Positive	M1 money supply	IFS of IMF	1999:01 to 2008:08
	ipi $(logY_{BD} - logY_{US})$	Negative	Industrial production index	IFS of IMF	1999:01 to 2008:08
	int $(log\ int_{BD} - log\ int_{US})$	Positive	Three month T-bill rate	IFS of IMF	1999:01 to 2008:08
	inf $(log\ inf_{BD} - log\ inf_{US})$	Positive	Consumer price index	IFS of IMF	1999:01 to 2008:08

The spot exchange rate is the number of BDT per USD. M1 proxies for money supply and the Industrial Production Index (IPI) proxies for real income variable. The interest rate is the three month T-bill rate. Moreover, I use Consumer Price Index (CPI) as a price measure. Table 1 shows the variables and their expected signs along with the proxy used and the sources of data.

Figure 1: Exchange rate, M1 money supply, IPI, interest rate and inflation rate scenario from 1999:01 to 2008:08

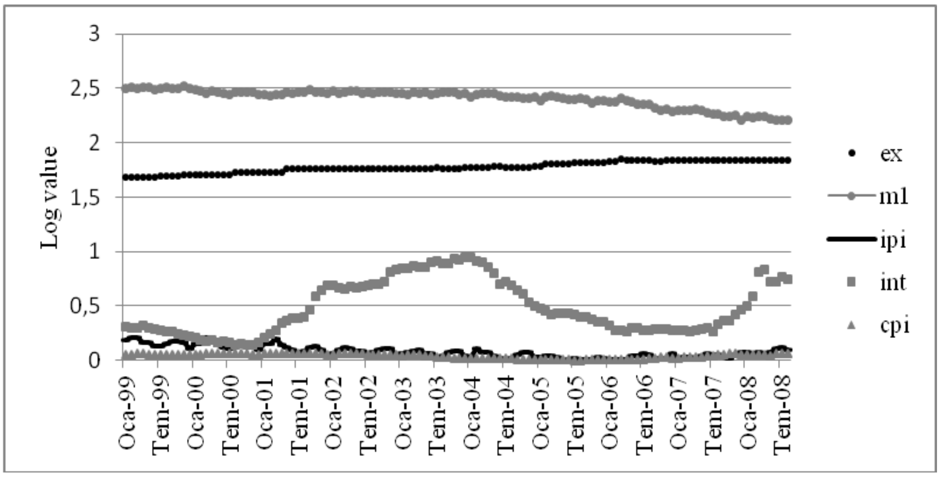

Figure 1 illustrates movements of exchange rate, M1 money supply, industrial production index, interest rate and inflation rate from 1999:01 to 2008:08.

4. Empirical models and results

4.1 Unit root test

Granger and Newbold (1974) and Philips (1986) show that using non-stationarity time series steadily diverging from long-run mean creates unreliable correlations within the regression analysis leading to unbounded variance process. For this reason, I use the Augmented Dickey-Fuller (ADF) unit root test to test the null hypothesis that the time series is non-stationary. Because, Dejong et al. (1989) show that an Augmented Dickey-Fuller type unit root test may have low power, I also use the Kwiatkowski, Phillips, Schmidt and Shin (KPSS) unit root test. The null hypothesis of the KPSS unit root test is that the time series is stationary which is opposite of the null hypothesis of ADF test. The Akaike Information Criterion (AIC) selects the optimal lag length for the ADF test and Kernel Based Criteria set out by Newey and West (1994) selects optimal bandwith for KPSS.

Table 2: Unit root test

Variable	ADF test with intercept	ADF test with trend & intercept	KPSS test with intercept	KPSS test with trend & intercept
ex_t	-1.45	-1.92	1.20*	0.10*
Δex_t	-10.87*	-10.94*	0.21	0.09
$M1_t$	1.02	-0.99	1.08*	0.29*
$\Delta M1_t$	-15.12*	-15.31*	0.42	0.07
ipi_t	-2.22	-1.87	1.09*	0.32*
Δipi_t	-11.70*	-12.15*	0.33	0.09
int_t	-1.30	-1.33	1.02*	0.90*
Δint_t	-6.58*	-6.55*	0.27	0.14
inf_t	-1.18	-0.45	2.68*	0.89*
Δinf_t	-6.79*	-7.01*	0.46	0.21

Note: * indicates 1% level of significance

Table 2 reports the results of unit root tests for BDT-US dollar exchange rate and other macroeconomic variables, in levels and first differences. In every case, the ADF test fails to reject the null hypothesis in the level form at 1% significance level. However, ADF unit root test reject the null hypothesis for all variables in first difference at 1% significance level.

KPSS unit root test rejects null hypothesis in the level form for the same variables at 1% significance level. But KPSS unit root test fail to reject the null hypothesis for all variables in first difference. So, both ADF and KPSS unit root test confirm that all the variables are 1st difference stationary form.

4.2 Cointegration and Johansen test

I use multivariate co-integration and a vector error correction model (VECM) to detect and estimate a long-run stationary relationship among the variables. According to Korap (2008), this methodology constructs an error correction mechanism among the same order integrated variables enabling that a stationary combination of the variables do not drift apart without bound even though all have been individually subject to non-stationary I(d) process, therefore, ruling out the possibility that estimated relationships tend to be spurious.

To determine the long-run cointegration relationship among the variables, I apply two likelihood tests: maximum eigenvalue and trace test. Cointegration means that despite being individually non stationary, a linear combination between two or more time series can be stationary. Cointegration of two (or more) time series suggests that there is a long run or equilibrium relationship between them. The multivariate cointegration test based on Johansen-Juselius is used to determine the long run relationship (Miankhel, Thangavelu and Kalirajan 2009). The testing hypotheses are the null of non-cointegration against the alternative that is the existence of cointegration by using the maximum likelihood procedure (Johansen and Juselius 1990). An autoregressive coefficient is used for modeling each of the variables (which is regarded as endogenous) as a function of all lagged endogenous variables of the model. The outline of Johansen test is given as follows:

If Z_t denotes a p $\times$ 1 vector of variables which are not integrated in order higher than one, then Z_t can be formulated as a Vector Autoregression (VAR) model of order k:

$$Z_t = \Pi_1 Z_{t-1} + \Pi_2 Z_{t-2} + ... + \Pi_k Z_{t-k} + \text{Deterministic components} + \varepsilon_{1t} \quad (5)$$

Where, ε_{1t} is independently and normally distributed and $\Pi_1, \Pi_2, ..., \Pi_{t-k}$ are coefficient matrices.

In order to apply the Johansen test a sufficient number of time lags are required. It is better to follow the relative procedure which is based on the calculation of likelihood ratio test statistics (Sims 1980). The trace test and maximum eigenvalue test to establish the number of cointegration vector is reported in table 3. The optimum lag length is five which is determined by using Akaike Information Criterion. Exchange rate equation under the assumption r=1 is as follows:

$$\begin{array}{lllll} & ex_t = 2.03\, M1_t & + 0.91\, ipi_t & - 0.19 int_t & + 2.42\, inf_t \\ t - value & (7.697) & (3.933) & (9.166) & (6.761) \end{array} \qquad (6)$$

According to table 3, the trace test indicates three cointegration vectors in the long run variable space. On the other hand, the eigenvalue test indicates one cointegration vector. In this condition, few researchers like to work with more than one cointegration vectors such as Dugler and Cin (2002) and other likes to work with common cointegration vector such as Korap (2008). According to Korap (2008), if researchers choose to work with more than one cointegration vectors then this may require the identification of the each vector to which different economic interpretations can be attributed. Besides, some other identification issues to obtain independent vectors from each other would be required. In this paper, I follow Korap (2008) and choose common vector.

From equation (6), I find that the relative money supply has a positive long run relationship with nominal exchange rate which is the common findings for all the models explaining monetary exchange rate determination. However, relative real income has a positive long run relationship with exchange rate which is not common finding. The inflation differential has a positive sign. Thus, the inflation depreciates domestic currency. Moreover, the negative sign on the interest differential supports the notion that relative interest differential appreciates the domestic currency rate.

According to Oskooee and Kara (2000) and Korap (2008), short run deviations from the fundamental based equilibrium course of nominal exchange rate have permanent impact on the long run equilibrium exchange rate. For Bangladeshi economy I get the same result since the adjustment coefficient of the exchange rate has a positive significant sign in table 3.

Table 3: Johansen co-integration test

Null hypothesis	**r=0**	**r≤1**	**r≤2**	**r≤3**	**r≤4**
Eigen value	0.35	0.24	0.22	0.15	0.001
λ trace	122.62*	75.39*	44.66*	17.79	0.16
5% critical value	79.34	55.25	35.01	18.40	3.84
λ max	47.23*	30.72	26.87	17.63	0.16
5% critical value	37.16	30.82	24.25	17.15	3.84

Unrestricted co-integration coefficients

EX	M1	IPI	INT	INF
74.20298	-150.8260	-67.16181	13.73248	-179.2437
-43.43950	4.680755	20.82218	-2.416380	-97.69053
114.6991	-0.178259	90.81783	5.545456	-72.40432
153.6007	-118.4637	1.053583	7.061407	-132.7803
79.04984	-19.53464	-23.97398	1.233012	-42.43347

Unrestricted adjustment coefficients

D(EX)	0.000931	0.001232	-0.001144	0.000430	-9.52E-05
D(M1)	0.004835	-0.001685	-0.000846	0.001420	-0.000304
D(IPI)	0.000735	-0.001436	-0.006242	0.002293	0.000416
D(INT)	-0.010220	-0.008634	-0.005313	0.000554	-0.000544
D(CPI)	-0.000721	0.000299	0.000343	0.000955	2.37E-05

1 Cointegrating Equation(s): Log likelihood 1818.369

standard error in parentheses

EX	M1	IPI	INT	INF
1.000000	-2.032614*	-0.905109*	0.185066*	-2.415586*
	(0.26409)	(0.23016)	(0.02019)	(0.35729)

Adjustment coefficients

D(EX)	0.069063***
	(0.03669)
D(M1)	0.358805*
	(0.09252)
D(IPI)	0.054512
	(0.14711)
D(INT)	-0.758370*
	(0.22966)
D(CPI)	-0.053492**
	(0.02305)

Note: Figures in parentheses are standard errors
* indicates significance at 1% level, ** indicates significance at 5% level and
*** indicates significance at 10% level

4.3 Vector error correction model

Table 4 reports the vector error correction model estimation. Table 4 also includes different types of diagnostic tests such as Doornik-Hansen test, heteroskedasticity test and serial correlation test.

Table 4: Vector error correction model (VECM)

Variable	Coefficient	Standard error	t-Statistics	P value
C	0.327385**	0.149893	2.1841	0.03294
EC(-1)	-0.14311**	0.065741	-2.1769	0.03350
D(ex)(-3)	-0.268789***	0.141584	-1.8984	0.06253
D(ex)(-4)	-0.256318***	0.140931	-1.8187	0.07403
D(ex)(-8)	0.258803***	0.145106	1.7835	0.07964
D(ex)(-9)	0.453039*	0.145647	3.1105	0.00288
D(m1)(-2)	0.127949**	0.0681001	1.8788	0.06521
D(m1)(-3)	0.1269***	0.0676213	1.8766	0.06552
D(m1)(-4)	0.150984**	0.0690096	2.1879	0.03265
D(ipi)(-1)	0.13121**	0.0678258	1.9345	0.05785
D(ipi)(-2)	0.124792**	0.0623908	2.0002	0.05009
D(ipi)(-3)	0.109191***	0.0607153	1.7984	0.07723
D(int)(-5)	0.0473377**	0.0217241	2.1790	0.03333
D(int)(-9)	-0.0487436***	0.0244582	-1.9929	0.05090
D(inf)(-1)	-0.347917	0.213615	-1.6287	0.10870
D(inf)(-6)	-0.285799	0.200933	-1.4224	0.16019
Mean dependent var	0.001332	S.D. dependent var	0.005107	
Sum squared resid	0.001334	S.E. of regression	0.004754	
R-squared	0.512989	Adjusted R-squared	0.133285	
Rho	-0.075235	Durbin-Watson	2.102208	
Doornik-Hansen test: Chi-square (8) = 6.9425 [0.5429] VEC Residual Heteroskedasticity Test: Chi-square(1410)=1439.393 [0.2870] VEC Residual Serial Correlation LM Test: LM(1)=30.273 [0.214] and LM(3)=28.306 [0.293]				

Note: * indicates significance at 1% level, ** indicates significance at 5% level and *** indicates significance at 10% level

This error correction model has good diagnostic tests. VEC residual serial correlation Lagrangian multiplier test is used for investigating possible serial correlation in the error term. The null hypothesis for this test is no serial correlation in the error term. Since the probability values for LM (1) and LM (3) are greater than 0.05, the residuals are not serially correlated. The p-value of VEC residual heteroskedasticity test is about 0.29. So it fails to reject the null hypothesis of no heteroskedasticity in the residuals. The Doornik-Hansen test also suggests that the residuals are normally distributed.

5. Forecasting performance

Accuracy of out-of-sample forecasting performance of a model is an essential indicator of its robustness. In this section, I try to evaluate the out-of-sample predictability of estimated model (basic monetary model). For this reason, I consider following benchmark models: random walk with drift and random walk without drift models. I compare forecasting performance of basic monetary model with these two benchmark models. I use forecast period from 2006:01 to 2008:08 in order to evaluate out-of-sample forecasting performance. I apply dynamic prediction instead of static prediction. This study uses two well-known criteria: root mean squared error (RMSE) criterion and forecast encompassing criterion to gauge the relative merits of each model.

5.1 RMSE criterion

Both Neely and Sarno (2002) and Korap (2008) use Theil's U statistics which implies the ratio of Root Mean Squared Errors (RMSEs) from two competing models. I also follow this methodology for evaluating out-of-sample predictability of models. I take the ratio of basic monetary model (BMM) and random walk with drift (RWD) and also the ratio of basic monetary model (BMM) and random walk without drift (RWWD). If ratio is less than one then it implies that estimated model has superior forecasting performance as compared to competing benchmark models.

In table 5, I find that basic monetary model is superior to random walk model in case of forecasting for 26 months. From 27th month random walk is superior in forecasting as compared to basic monetary model. This implies that knowledge of co-integration can improve the forecasting performance within the 26 months.

Table 5: Forecasting comparisons

BMM/RWD out sample forecasting comparison		BMM/RWWD out sample forecasting comparison	
Forecast period	BMM/RWD ratio	Forecast period	BMM/RWWD ratio
1	0.845	1	0.847
2	0.809	2	0.814
3	0.809	3	0.817
4	0.805	4	0.816
5	0.805	5	0.819
6	0.799	6	0.816
7	0.786	7	0.805
8	0.778	8	0.800
9	0.773	9	0.797
10	0.783	10	0.811
11	0.793	11	0.824
12	0.801	12	0.835
13	0.810	13	0.847
14	0.816	14	0.857
15	0.823	15	0.867
16	0.829	16	0.876
17	0.834	17	0.884
18	0.839	18	0.892
19	0.848	19	0.905
20	0.857	20	0.918
21	0.865	21	0.930
22	0.875	22	0.943
23	0.883	23	0.955
24	0.892	24	0.968
25	0.900	25	0.980
26	0.907	26	0.991
27	0.915	27	1.002
28	0.923	28	1.015
29	0.932	29	1.027
30	0.940	30	1.040
31	0.948	31	1.052
32	0.956	32	1.064

5.2 Forecast encompassing criterion

In order to perform encompassing test between BMM and RWD, forecast and forecast error of both models need to compute. I perform the following regressions to assess the relative merits of these two models. If the t value of γ is insignificant and the t value of α is significant, BMM forecast encompasses RWD. It means that BMM contains more useful information than that contained in the forecasts generated by RWD.

$$e(t)^{BMM} = \gamma[g(t)^{RWD} - g(t)^{BMM}] + \varepsilon_t \quad (7)$$

$$e(t)^{RWD} = \alpha[g(t)^{BMM} - g(t)^{RWD}] + u_t \quad (8)$$

I also perform the following regressions to execute encompassing test between BMM and RWWD.

$$e(t)^{BMM} = \gamma[g(t)^{RWWD} - g(t)^{BMM}] + v_t \quad (9)$$

$$e(t)^{RWWD} = \alpha[g(t)^{BMM} - g(t)^{RWWD}] + e_t \quad (10)$$

Table 6: Forecast encompassing comparisons

Models name	BMM	RWD	RWWD
BMM	…	-0.0614 (0.0588)	-0.0502 (0.0575)
RWD	-1.5110* (0.3606)	…	…
RWWD	-0.0012* (0.0003)	…	…

Note: * indicates significance at 1% level and figures in parentheses are standard errors

Table 6 shows that estimated model (BMM) forecast encompasses both RWD and RWWD model (both coefficients are not statistically significant). On the other hand, Both RWD and RWWD forecasts fail to encompass BMM model (statistically significant coefficients). This paper does not consider the encompassing test between RWD and RWWD since it is outside of the scope of the study.

6. Conclusion

In this paper, I try to use Johansen cointegration technique and I find that nominal exchange rate is cointegrated with mentioned macroeconomic variables. Empirical findings show that relative real income has statistically significant positive long run relationship with nominal exchange rate and inflation differential can create currency depreciation of Bangladesh. Moreover, I find that the relative interest rate differential in favor of Bangladesh creates appreciation of BDT.

I also identify that for Bangladesh short run deviations from the fundamental based equilibrium course of nominal exchange rate have permanent impact on the long run equilibrium exchange rate. In case of forecasting performance, I find that estimated basic monetary model is better than random walk with drift and without drift model for around two years of forecasting horizons. As a result, I can say that cointegration relationship knowledge helps to improve the forecasting performance of the exchange rate determination model.

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