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Research Paper

Forecasting the Rupee-Dollar Exchange Rate Using the Monetary Model

Economics

KEYWORDS : Forecasting, Exchange Rate, Monetary Model

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ABSTRACT

We use the monetary model of exchange rate determination to generate in-sample and out-of-sample forecasts of the Rupee-Dollar exchange rate. The assumptions of flexible prices and maintenance of Purchasing Power Parity implies that the domestic price level and the exchange rate are endogenously determined given the money supply policy. We undertake simultaneous equation estimation with the nominal exchange rate and the consumer price index as the endogenous variables using the two-stage least squares procedure. The estimated parameters were then used to generate in-sample and out-of-sample forecasts and compared with actual values.

1. INTRODUCTION

The monetary approach to exchange rates, which assumes that the prices of goods are perfectly flexible, implies that a country's currency depreciates when its nominal interest rates rise because of higher expected future inflation.

Let us consider as an illustration, the effect of an (exogenous) future money supply growth rate by amount Δm (by the Reserve Bank of India). The Fisher Effect tells us that a rise in Δm in the future money supply growth rate will raise the nominal interest rate on rupees from r1 to r2 = r1 + Δm. An increase in the nominal Rupee interest rate reduces money demand and therefore requires an equilibrating fall in the real money supply. But the nominal money stock is unchanged in the short run because it is only the future rate of the Indian money supply growth that has risen. Given the unchanged nominal money supply, M_1, an upward jump in India's price level from P_1^{Ind} to P_2^{Ind} brings about the needed reduction in Indian real money holdings. The assumed flexibility of prices allows this jump to occur even in the short run.

So then what happens to the Rs/ $ exchange rate?

The monetary approach assumes Purchasing Power Parity (PPP), implying that as P^{Ind} rises (while the US Price level remains constant, being exogenous) the Rs/ $ exchange rate must rise (a depreciation of the Rupee). So from the PPP we have:

$$E_{Rs/\$} = \frac{P_{Ind}}{P_{US}} = \frac{M_{India}/P_{US}}{M_{India}/P_{india}}$$

Thus, when goods prices are perfectly flexible, the money market equilibrium implies two effects of an increase in money supply:

1. the rupee interest rate increases from r1 to r2 = r1 + Δm, in line with the Fisher Effect.

2. India's price level jumps from P_1^{Ind} to P_2^{Ind} .

By PPP this requires a depreciation of the Rupee against the $ implying Rs/ $ exchange rate increasing from E_1 to E_2. So we have the phenomenon wherein the Rupee depreciates despite the rise in the Indian interest rates. Intuitively, this is because higher expected future monetary growth implies faster expected depreciation of the Rupee against the $, and therefore, a rise in the attractiveness of Rupee deposits. It is that change in expectations that leads simultaneously to a rise in the nominal interest rate on the Rupee and to a depreciation of the rupee in the foreign exchange market.

II. MODEL ESTIMATION

I use quarterly data taken from the website of Reserve Bank of India. The primary estimation is carried out using quarterly data over the ten period from 1993:3 to 2003:2. The out-of-sample forecasts are generated for the period 2003:3 to 2006:2. I started by estimating a specification with three endogenous variables : $\log(NER_t)$, $\log(CPI_t)$ and TB_t , however, when the Hausman test was conducted, the residual from the regression of TB on all the exogenous variables was found to be insignificant in the auxiliary regression with $\log(NER_t)$ as the regressand. So I chose to work with the following system :

(1) $\log(NER_t) = a_1 + a_2 \log(NER_{t-1}) + a_3 \log(CPI_{t-1}) + a_4 TB_t + a_5 \log(GFD_t) + e_{1t}$

(2) $\log(CPI_t) = b_1 + b_2 \log(NER_{t-1}) + b_3 \log(CPI_{t-1}) + b_4 IIP_t + b_5 \log(GFD_t) + b_6 \log(MS_t) + e_{2t}$

Endogenous variables : $\log(NER_t)$, $\log(CPI_t)$

Exogenous Variables : $\log(NER_{t-1})$, $\log(CPI_{t-1})$, TB_t , $\log(GFD_t)$, IIP_t , $\log(MS_t)$

Table 1
IDENTIFICATION TABLE

equation	1	$\log NER_t$	$\log CPI_t$	$\log NER_{t-1}$	$\log CPI_{t-1}$	TB_t	$\log GFD_t$	IIP_t	$\log MS_t$
1	a_1	1	0	a_2	a_3	a_4	a_5	0	0
2	b_1	b_2	1	0	b_3	0	b_5	b_4	b_6

Table 2
ORDER CONDITION

Equation	Endogenous included – 1	Exogenous excluded	Result
1	1 – 1 = 1	2	Over identified
2	2 – 1 = 1	2	Over identified

Order Condition satisfied.

Rank Condition

Table 3
Equation 1
Exogenous variables excluded : IIP_t , $\log(MS_t)$

b_4
b_6

Thus there exists atleast one non-zero 1*1 matrix.

Table 4
Equation 2
Exogenous variables excluded : $\log(NER_{t-1})$, TB_t

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a_2
a_4

Thus there exists at least one non-zero 1*1 matrix.

Rank Condition satisfied.

HAUSMAN TEST

Regressing log(CPI_t) on all the exogenous variables, viz. log(NER_{t-1}) , log(CPI_{t-1}) , TB_t , log(GFD_t) , IIP_t , log(MS_t) produced the following result :

Table 5

Dependent Variable: LOG(CPI_IND)				
Method: Least Squares				
Date: 01/25/07 Time: 22:57				
Sample(adjusted): 1993:4 2003:2				
Included observations: 39 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.884489	0.408090	-2.167388	0.0378
LOG_NER_LAG	-0.024233	0.099989	-0.242352	0.8101
LOG_CPI_IND_LAG	0.980584	0.086294	11.36324	0.0000
TBILL_IND	0.000386	0.001514	0.255264	0.8002
IIP_IND	-0.001628	0.000562	-2.893608	0.0068
LOG_GFD	-0.006364	0.005741	-1.108528	0.2759
LOG_M3_IND	0.094773	0.043863	2.160643	0.0383
R-squared	0.994849	Mean dependent var		5.945251
Adjusted R-squared	0.993883	S.D. dependent var		0.195589
S.E. of regression	0.015297	Akaike info criterion		-5.361131
Sum squared resid	0.007488	Schwarz criterion		-5.062543
Log likelihood	111.5421	F-statistic		1030.021
Durbin-Watson stat	1.636598	Prob(F-statistic)		0.000000

Then I conducted the following **auxilliary regression:**

log(NER_t) = c_1 + c_2 log(NER_{t-1}) + c_3 log(CPI_{t-1})+ c_4 TB_t + c_5 log(GFD_t) + c_6 res

where

res = residual series obtained from the regression of log(CPI_t) on all exogenous variables above.

Table 6

Dependent Variable: LOG(NER)				
Method: Least Squares				
Date: 01/25/07 Time: 23:10				
Sample(adjusted): 1993:4 2003:2				
Included observations: 39 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.253118	0.134136	-1.887017	0.0680
LOG_NER_LAG	0.766531	0.097805	7.837378	0.0000
LOG_CPI_IND_LAG	0.193667	0.075005	2.582075	0.0144
TBILL_IND	0.001429	0.001673	0.854279	0.3991
LOG_GFD	-0.003987	0.005828	-0.684019	0.4987
RES	0.256003	0.208516	1.227738	0.2282
R-squared	0.989067	Mean dependent var		3.681935
Adjusted R-squared	0.987410	S.D. dependent var		0.160812
S.E. of regression	0.018044	Akaike info criterion		-5.051386
Sum squared resid	0.010744	Schwarz criterion		-4.795454
Log likelihood	104.5020	F-statistic		597.0592
Durbin-Watson stat	1.402208	Prob(F-statistic)		0.000000

The p-value of the coefficient for res in the above auxiliary equation is 0.2282 indicating the presence of simultaneity. Thus, OLS of the equation for log(NER_t) would yield inconsistent estimates. So, I estimated the system using the two-stage-least squares procedure to obtain consistent parameter estimates.

Two-Stage-Least Squares System Specification :

log(ner)=c(1)+c(2)*log(ner(-1))+c(3)*log(cpi_ind(-1))+c(4)*tbill_ind+c(5)*log(gfd)

log(cpi_ind)=c(6)+c(7)*log(cpi_ind(-1))+c(8)*iip_ind+c(9)*log(gfd)+c(10)*log(m3_ind)+c(11)*log(ner)

Instrumental Variables :

log(ner(-1)) log(cpi_ind(-1)) tbill_ind iip_ind log(gfd) log(m3_ind)

ESTIMATION OUTPUT

Table 7

System: SYS01				
Estimation Method: Two-Stage Least Squares				
Date: 01/26/07 Time: 21:08				
Sample: 1993:4 2003:2				
Included observations: 39				
Total system (balanced) observations 78				
Instruments: LOG(NER(-1)) LOG(CPI_IND(-1)) TBILL_IND IIP_IND				
LOG(GFD) LOG(M3_IND) C				
	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.253118	0.135134	-1.873094	0.0654
C(2)	0.766531	0.098532	7.779551	0.0000
C(3)	0.193667	0.075562	2.563023	0.0126
C(4)	0.001429	0.001685	0.847976	0.3995
C(5)	-0.003987	0.005872	-0.678973	0.4995
C(6)	-0.857124	0.404307	-2.119981	0.0377
C(7)	0.992471	0.100886	9.837542	0.0000
C(8)	-0.001617	0.000561	-2.883609	0.0053
C(9)	-0.006522	0.005570	-1.171004	0.2457
C(10)	0.089493	0.038788	2.307253	0.0241
C(11)	-0.028657	0.125432	-0.228468	0.8200

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Determinant residual covariance		5.31E-08	
Equation: LOG(NER)=C(1)+C(2)*LOG(NER(-1))+C(3)*LOG(CPI_IND(-1))			
+C(4)*TBILL_IND+C(5)*LOG(GFD)			
Observations: 39			
R-squared	0.988567	Mean dependent var	3.681935
Adjusted R-squared	0.987222	S.D. dependent var	0.160812
S.E. of regression	0.018178	Sum squared resid	0.011235
Durbin-Watson stat	1.252848		
Equation: LOG(CPI_IND)=C(6)+C(7)*LOG(CPI_IND(-1))+C(8)*IIP_IND			
+C(9)*LOG(GFD)+C(10)*LOG(M3_IND)+C(11)*LOG(NER)			
Observations: 39			
R-squared	0.994754	Mean dependent var	5.945251
Adjusted R-squared	0.993960	S.D. dependent var	0.195589
S.E. of regression	0.015201	Sum squared resid	0.007625
Durbin-Watson stat	1.629285		

Coefficients have the expected signs, most of them are significant, adjusted-R-Squared for both the equations is high. Also, serial correlation is low as indicated by the Dubin-Watson statistics.

Thus, I generated the ex-poste forecasts using this method.

III. FORECAST RESULTS

Table 8

Measures of Accuracy

Forecast Horizon	1 quarter ahead	2 quarter ahead	3 quarter ahead	4 quarter ahead
ME	-0.65276	-1.11294	-1.70972	-2.35754
MAE	1.043153	1.423629	2.035438	2.381773
RMSE	1.202202	1.81085	2.346049	2.723456
MPE	-1.46004	-2.50184	-3.85629	-5.30672
MAPE	2.315176	3.187834	4.575277	5.36131
RMSPE	2.67026	4.061735	5.280803	6.143592
U2	1.191625	1.442471	1.528243	1.755493

Plot of the forecasted versus actual values

Figure 1

1 Quarter Ahead Forecasts

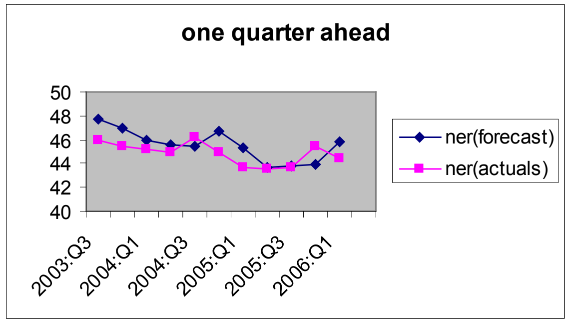


Figure 2

2 Quarter Ahead Forecasts

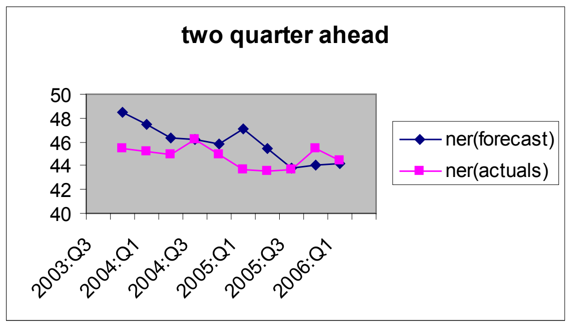


Figure 3

3 Quarter Ahead Forecasts

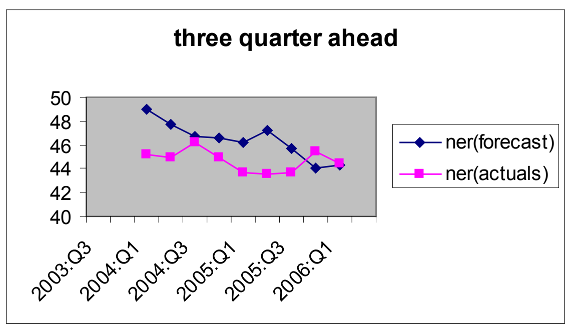
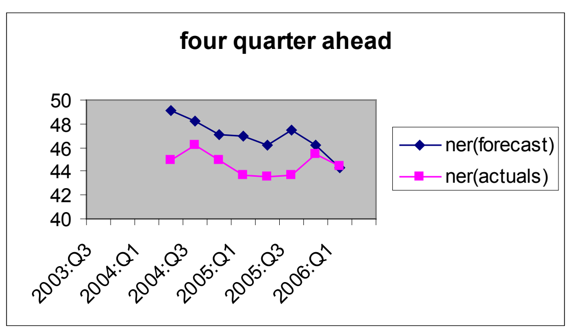


Figure 4

4 Quarter Ahead Forecasts



Clearly the forecast accuracy deteriorates with forecast horizon. Also, the apparent in-sample success does not translate into out-of-sample forecasting performance, consistent with estimation bias.

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