Exchange Rate Predictability Using Macro Variables: A Study on India

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Abstract

In this paper we study the predictability of exchange rate return of India using macro variables such as money supply growth, stock price returns, inflation rate, foreign investment, trade balance, foreign exchange reserve etc., which have been found to be relevant in similar studies concerning other, mostly developed, economies and / or which are considered to be important in theoretical studies on exchange rate. The full set of macro variables used, to begin with, comprises 24 variables. Inferences on predictive ability of each of these variables are based on recently developed out-of-sample tests of predictive ability due to West (1996), Clark and McCracken (2001) and McCracken (2004). In this selection procedure, specific-to-general as well as general-to-specific approaches of model selection are used, and we also check our results using a data-mining-robust bootstrap procedure. Thereafter, we use the macro variables which are thus found to have significant predictive ability and obtain a model for exchange rate return of India in linear dynamic regression framework, and then carry out all relevant diagnostic tests on the residuals of this model.

Keywords: exchange rate return, general-to-specific model selection criterion, out-of-sample forecasts, predictability, specific-to-general model selection criterion.

***JEL Classification**:* F31, C22, C53

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1. Introduction

Economists have imputed a lot of importance on theoretical exchange rate models. Over the years, a large number of such models have been developed. These models are based primarily on the relationship between exchange rate and relevant macroeconomic variables, and usually referred to as structural models. After the publication of the two seminal papers by Meese and Rogoff (1983a,b), where they observed that a simple random walk model forecasts better than the more complex structural models, several alternative models have been developed. There have been evidences as well that if structural models are generalized to include lagged adjusted mechanisms (see, for instance, Somanath (1986) and Edison (1991)), or in case their parameters are allowed to vary over time as in Schinasi and Swamy (1989) and De Arcangelis (1992), their forecasts can be somewhat improved. Further, Hogan (1986), Chinn and Meese (1995) and Kim and Mo (1995) have shown that while time series models may be superior in short-run, structural models may perform quite well over long-run. Others have stressed the relevance of economic fundamentals such as money supply and real income in determining exchange rate behaviour, and reaffirmed the superiority of structural models over the random walk model - at least for medium and long-run horizons.

In this paper, we are interested in empirical determination and forecastability of India's monthly exchange rate return using various macroeconomic variables. Now, one of the most important issues in such a study is the identification of the macroeconomic variables (henceforth to be referred to as macro variables) which are likely to be relevant in predicting exchange rate return. More so because all such studies which have been carried out mostly for the developed economies, have not found, as expectedly, the same set of macro variables to be relevant. To that end, the mixed results in the extant literature make it difficult, on the whole, to determine which particular macro variables are reliable indicators of exchange rate return.

To deal with this problem, we have considered, in this paper, both in-sample and out-of-sample tests of return predictability. While the in-sample analysis employs what is known in statistical / econometric literature as predictive regression framework, the out-of-sample forecasts are analyzed using a pair of recently-developed-and potentially more powerful tests due to Clark and McCracken (2001) and McCracken (2004). The test statistics of these two tests are due to Diebold and Mariano (1995) and West (1996) and Harvey *et al.* (1998) (see also Rapach *et al.* (2005), for some relevant details). Another aspect to such a study is data mining. Since our interest is in testing the predictive ability of a large number of macro variables in turn, it is only natural that the issue of data mining would arise. The conventional wisdom holds that out-of-sample tests help guard against data mining. However, it has been recently argued that both the in-sample and out-of-sample tests are equally susceptible to data mining and the only way we can account for this data mining problem is by using an appropriate bootstrap procedure. We have followed the bootstrap procedure used by Rapach *et al.* (2005) and Rapach and Wohar (2005), which are originally due to Nelson and Kim (1993), Mark (1995), Kothari and Shanken (1997) and Kilian (1999), to find the macro variables which significantly explain India's exchange rate return series.

As regards the set of macro variables to start with, we consider what may be taken to be a set of 'standard' relevant macro variables. Based on the extant empirical literature, the set comprises Bombay stock exchange sensitivity index (BSESENSEX), call money rate (CMR), M0 (this variable is a component of the stock of money, basically defined as the reserve money), M1 defined as the *narrow money,* M3 (*Broad money),* consumer price index (CPI), wholesale price index (WPI), foreign currency asset (FCA), total reserve of foreign exchange (TR), industrial production (IP), export (EX), import (IM), trade balance (TB), gross fiscal deficit (GFD), sale/purchase of US dollar (SPUSD), open market operations (OMO), Federal funds rate (FFR), six-month treasury bill rate of US (TBRU6), three-month treasury bill rate of US (TBRU3), NASDAQ, world gold price

(WGP), foreign direct investment (FDI), foreign institutional investment (FII), total foreign investment (FINV).

While the effects of a rise in domestic and foreign money supply, interest rate and inflation rate, industrial production (a proxy of output) and trade balances on exchange rate are pretty straightforward due to the various theories which have developed over time, the effects of the other variables might not be easy to explain, especially because the number of studies in the latter category is very limited even in developed economies. For example, recently some studies have tried to deal with the relation between exchange rate and stock prices. It has been found that domestic stock returns have a positive effect on exchange rate since higher stock prices indicate better performance of the economy and this attracts foreign funds which lead to appreciation of the domestic exchange rate (Ki-Ho-Kim (2003)). Some other studies in this direction are due to Aggarwal (1981), Soenen and Hennigar (1988), Ma and Kao (1990), Roll (1992) Abdalla and Murinde (1997), Chow *et al.* (1997), Ajayi *et al.* (1998), Nieh and Lee (2001), Phylaktis and Ravazzolo (2005) and Pan *et al.* (2006). Insofar India is concerned, the relationship between stock index and exchange rates has been studied by Mishra (2004) and Damele *et al.* (2004).

The effect of yet another important macro variable, the budget deficit on exchange rate, has been studied by Nyahoho (2006) where he has shown that there is no relationship between the two using statistical and empirical analyses based on data from the OECD countries. He carried out a regression of first difference of exchange rate and budget deficit in order to reach to this conclusion.

The role of foreign direct investment growth of an economy has also been studied in great detail by Alfaro *et al.* (2004). This is an important variable for study on foreign exchange rate as this macro variable is often assumed to influence the return on foreign exchange rate. An increase in foreign investment or its components should obviously lead to an appreciation of domestic currency due to inflow of foreign funds.

As regards the relationship between interest rate market and foreign exchange market, it is known that these are closely linked as there exists arbitrage opportunities between the two markets. However, monetarists assert that an increase in domestic interest rate (essentially increasing the interest rate differential) will decrease the real demand for money, and given a fixed nominal money supply, this will be achieved by a rise in domestic price level and hence a depreciation of exchange rate. Hence, this effect is opposite to the standard Keynsian model with incorporated capital mobility, as described by Mundell (1968) and Fleming (1962) where a rise in interest rate leads to an appreciation of the domestic currency. This latter result is often viewed as a short-run result where the prices are considered to be sticky. There have been some works which have tried to study the relationship between exchange rate and interest rate, but these have been mostly in terms of testing uncovered interest parity.

Ramachandran (2006) has made a comprehensive study of foreign exchange reserves of India. He has found that the asymmetric control over capital inflows and asymmetric intervention in favour of strengthening export competitiveness in an era of persistent capital inflows seem to be responsible for the stockpile of reserves in India. The study by Kasman and Ayhan (2007) is another recent one where the long run relationship between exchange rate and reserves has been studied.

Tarhan (1995) has empirically investigated the effect of Federal Reserve open market operations (OMO) on both short-term and long-term interest rates along with the influence of OMO on the stock markets and exchange rate markets. Very recently, another probable variable that has been identified to affect exchange rate is the Federal funds rate or short term interest rate of the US. The effects of US interest rate shocks on the economies of other developed countries have been studied by Kim and Roubini (2000), and the general observation is that a rise in Federal funds rate is accompanied with devaluation of other world currencies. However, there are no such studies on the relationship between Federal funds rate and Indian exchange rate. Keeping this is mind, we have included Federal funds rate as an independent macro variable in determining the model for India's monthly exchange rate.

It is well known that quite often the central banks of the countries have to intervene in the exchange rate market to influence its movement towards some desired direction. In case of India, the most important instrument of the Reserve Bank of India (RBI) which is the central bank of India, is to directly intervene in this market by means of sale/purchase of US dollars. A purchase of US dollars is done to depreciate the domestic currency while it is sold when a depreciation of the domestic currency is to be countered. Another proxy of central bank intervention often used in studies is the change in foreign exchange reserves. Such macro variables are likely to affect modelling of exchange rate and its predictability. Further, sometimes the government might choose to sterilize the intervention made by them in the foreign exchange market. This may be done using the open market operations. Hence, this variable may also play some role in predictability of exchange rate return. Some important works on intervention are due to Bonser-Neal (1996), Baillie and Osterberg (1997), Chang and Taylor (1998), Dominguez (1998) and Nagayasu (2004). Kim and Sheen (2006) has carried out a recent study which tests the effectiveness of Bank of Japan's foreign exchange intervention on the conditional first and second moments of exchange rate return and traded volumes using a bivariate EGARCH model of the Japanese yen / US dollar market. For a comprehensive survey of theoretical and empirical literature on foreign exchange rate intervention, see Edison (1993), Almekinders (1995), Sarno and Taylor (2001) and Frankel *et al.* (2004).

In India, there have been some empirical studies on the effect of intervention on foreign exchange rate. Bhaumik and Mukhopadhyay (2000) have considered a specification to link central bank's direct interventions in the foreign exchange market with changes in the country's exchange rate using the Mundell-Fleming model. Ghosh (2002) has used a Tobit and logit model for studying the role of intervention on exchange rate using daily data. Baig *et al.* (2003) have formulated and estimated a small open economy where a measure of exchange market pressure and an index of intervention activity have been constructed. The analysis of these two parameters highlights the fact that the RBI prefers to accommodate rupee[1] depreciation, while aggressively preventing appreciation. The net sale of foreign exchange is only resorted to in times of crises. The large amount of foreign exchange reserves that the RBI has built up bears ample testimony to its intervention in the foreign exchange market.

Other than intervention, the RBI also acts as the banker of last resort where it injects funds into the system to help participants tide over temporary mismatches of funds. This was implemented through the Liquidity Adjustment Facility (LAF) which was made effective on the 5th of June 2000. The system is being implemented in phases and currently is a daily exercise in which banks and primary dealers (PD) participate. Here the RBI conducts an auction system of repos (the rates at which RBI borrows from the banks) and reverse repos to suck-out and inject liquidity to the market. The exact quantum of liquidity to be absorbed or injected and the accompanying repo and reverse repo rates are determined by the Financial Markets Committee after taking into consideration the liquidity conditions in the market, the interest rate situation and the stance of monetary policy. Thus, the values of repos and reverse repos can help in explaining exchange rate. However, we could not use this variable in our analysis since this time series is available only from 2000 while our study uses all the data sets starting from 1994.

In addition to analyzing the predictive ability of each macro variable in turn, we also apply a procedure that combines general-to-specific model selection with out-of-sample tests of forecasting ability. The findings of these two procedures are combined for the purpose of identifying the set of appropriate macro variables for predicting the foreign exchange rate for India.

Once the macro variables have been identified, we check if the conditional mean thus assumed is correctly specified. This is so because it is now well-known that inferences based on models suffering from misspecification could be misleading and

[1] Rupee is the name of India's currency.

incorrect. For linear dynamic models, notable cases of such misspecifications include failing to take account for parameter instability, residual autocorrelations, misspecification of functional forms and omitted variables. It is worthwhile to note that an incorrectly specified conditional mean might as well lead to misspecification of conditional variance, provided, of course, volatility is found to be significant in the monthly exchange rate data.

Thus, the focus in the latter part of the paper - after including adequate lags to take care of autocorrelation in the return series – is on the aspect of specification, and to that end, we carry out appropriate tests for detecting parameter stability as well as functional form misspecification and omission of other relevant variables which might not have been included in the mean function by both the specific-to-general and general-to-specific approaches for selection of macro variables, and then take appropriate steps to guard against misspecification in the mean function in case the test rejects the null hypothesis of no misspecification of conditional mean. Thereafter, standard residual-based diagnostic tests including the BDS test (Brock *et al.* (1996)) are performed to detect the presence of second as well as other higher order dependences in the errors of the chosen model.

The paper is organized as follows. The methodology applied in this study is briefly described in the next section. Section 3 presents a brief description of the data sets used in our analysis. Empirical findings are discussed in Section 4. The paper ends with some remarks in Section 5.

2 Methodology and the final model

A number of econometric tools have been used in this study to determine the relevant macro variables which have predictive ability for exchange rate return, and also to test for misspecification of the final model thus obtained. We first discuss the details regarding the former. To that end, we first describe the predictive regression approach and the tests of predictability based on out-of-sample forecasting performance of the predictive regressions.

2.1 Predictive regression and out-of-sample tests of predictability

As stated in the preceding section, the selection of the macro variables is done by analyzing the predictive ability of each macro variable in turn, using predictive regression and then combining these findings with those obtained by the general-to-specific model selection procedure with out-of-sample tests of forecasting ability. In predictive regression, the predictive ability of a stationary variable is studied with a regression model having one regressor at a time. This model takes the form,

$$y_{t+1}^{k} = \alpha + \beta z_t + \gamma y_t + u_{t+1}^{k} \qquad (1)$$

where y_t is the return on exchange rate from period *t*-1 to period *t*, $y_{t+1}^{k} = y_{t+1} + ... + y_{t+k}$ is the return from period t to $t + k$, k is the forecast horizon, z_t is a stationary macro variable believed to potentially predict future returns on exchange rate, and u_{t+1}^{k} is the disturbance term. It maybe noted that a lagged return term has been included in (1) as a control variable since it is often found that the first lag is significant and quite adequate to describe the autocorrelations in foreign exchange return. The return on foreign exchange rate can be perceived as return that agents get from holding foreign currency. Under the null hypothesis $\beta = 0$, this variable does not have any predictive power for future returns while under the alternative hypothesis $\beta \neq 0$, z_t has predictive power for future returns. We have *T* observations on y_t and z_t of which *T*-*k* observations are usable and these are used to estimate the in-sample predictive regression model as well as for out-of-sample forecasting.

The predictive ability of z_t in the predictive regression framework is assessed by means of the *t*-statistic corresponding to $\hat{\beta}$, the ordinary least squares (OLS) estimate of β, as well as the goodness-of-fit measure R^2. The problems associated with estimating a predictive regression model like (1) are small sample bias and overlapping observations. The latter problem is often dealt with by using the standard errors proposed by Newey and West (1987), as these are robust to heteroskedasticity and serial correlation in the disturbance term. In spite of using robust standard errors to compute *t*-statistics, there can be serious size distortions when basing inferences on standard asymptotic distribution theory. To guard against size distortions, we base inferences on the concerning β in (1) on bootstrap procedures similar to Nelson and Kim (1993), Mark (1995), Kothari and Shanken (1997) and Kilian (1999).

As regards out-of-sample tests of predictability, we first need to have the out-of-sample forecasts, and these are obtained based on recursive scheme where the total sample of observations is divided into in-sample (say, the first *R* observations for y_t and z_t) and out-sample portions (the remaining ones). The first out-of-sample forecast for the unrestricted model (i.e., where $\beta \neq 0$) is generated in the following way. The unrestricted predictive regression model is first estimated by the OLS method using data available through *R*. Let these estimates be denoted as $\hat{\alpha}_{1,R}$, $\hat{\beta}_{1,R}$ and $\hat{\gamma}_{1,R}$. Using these estimates, forecast is generated for the next i.e., (*R*+1)*th* observation and hence the forecast error, denoted as $\hat{u}^k_{1,R+1}$. Similarly, the initial forecast for the restricted model (i.e., where $\beta = 0$) is generated and denoted as $\hat{u}^k_{0,R+1}$. A second set of forecasts is generated by updating the above procedure one period by using data available through period *R*+1 and using the estimates obtained from the restricted and unrestricted predictive regression models. The forecast errors thus obtained are $\hat{u}^k_{1,R+2}$ for the unrestricted model and $\hat{u}^k_{0,R+2}$ for the restricted model. This process is repeated through the available sample, and thus are obtained two sets of *T*-*R*-*k*+1 recursive forecast errors-one each for the unrestricted and restricted regression models ($\{\hat{u}^k_{1,t+1}\}^{T-k}_{t=R}$ and $\{\hat{u}^k_{0,t+1}\}^{T-k}_{t=R}$).

Now, in order to be able to infer on the predictive ability of z_t, we need to compare between the out-of-sample forecasts from the unrestricted and restricted predictive regression models. If the unrestricted model forecasts are superior to the restricted model forecasts, then the variable z_t improves the out-of-sample forecasts of y_{t+1}^k relative to the first order autoregressive (AR) benchmark model where z_t is excluded. To this end, Theil's U, the ratio of the unrestricted model forecast root-mean-squared error (RMSE) to the restricted model forecast RMSE is used as a descriptive measure; $U < 1$ implies that the unrestricted model forecast RMSE is less than the restricted model forecast RMSE and hence performance of unrestricted model in terms of forecasting is better. A more formal test to find out whether the unrestricted regression model forecasts are significantly superior to the restricted regression model forecasts involves using the McCracken (2004) *MSE-F* and Clark and McCracken (2001) *ENC-NEW* test statistics. Of the two, the first test statistic is a variant of the test statistics proposed by Diebold and Mariano (1995) and West (1996) to test for equal predictive ability, and the second is a variant of Harvey *et al.* (1998) test statistic for testing forecast encompassing.

MSE-F statistic: The *MSE-F* statistic is used to test the null hypothesis that the unrestricted model forecast mean squared error (MSE) is equal to the restricted model forecast MSE against the one-sided (upper-tail) alternative hypothesis that the unrestricted model forecast MSE is less than the restricted model forecast MSE. The *MSE-F* statistic is based on the loss differential, $\hat{d}_{t+1}^k = (\hat{u}_{0,t+1}^k)^2 - (\hat{u}_{1,t+1}^k)^2$. Letting

$\bar{d} = (T - R - k + 1)^{-1} \sum_{t=R}^{T-k} \hat{d}_{t+1}^k = M\hat{S}E_0 - M\hat{S}E_1$

where $M\hat{S}E_i = (T - R - k + 1)^{-1} \sum_{t=R}^{T-k} (\hat{u}_{i,t+1}^k)^2$, $i = 0,1$, the McCracken (2004) *MSE-F* statistic is given by

$$MSE - F = (T - R - k + 1)\bar{d} / M\hat{S}E_1 . \qquad (2)$$

A significant *MSE-F* statistic indicates that the unrestricted model forecasts are statistically superior to those of the restricted model. McCracken (2004) has shown that when comparing forecasts from nested models and for $k = 1$, the *MSE-F* statistic has a non-standard limiting distribution. Further, Clark and McCracken (2004) have demonstrated that the *MSE-F* statistic has a non-standard and non-pivotal limiting distribution in the case of nested models and for $k > 1$, and accordingly they have recommended basing inference on bootstrap procedure along the lines of Kilian (1999).

ENC-NEW statistic: The other out-of-sample statistic, *ENC-NEW*, relates to the concept of forecast encompassing. The *ENC-NEW* statistic due to Clark and McCracken (2001) takes the form,

$$ENC-NEW = (T - R - k + 1)\bar{c} / M\hat{S}E_1 \tag{3}$$

where $\bar{c} = (T - R - k + 1)^{-1} \sum_{t=R}^{T-k} \hat{c}_{t+1}^{k}$ and $\hat{c}_{t+1}^{k} = \hat{u}_{0,t+1}^{k}(\hat{u}_{0,t+1}^{k} - \hat{u}_{1,t+1}^{k})$.

Under the null hypothesis, the weight attached to the unrestricted model forecast in the optimal composite forecast is zero and the restricted model forecasts encompass the unrestricted model forecasts. Under the one-sided (upper-tail) alternative hypothesis, the weight attached to the unrestricted model forecast in the optimal composite forecast is greater than zero, so that the restricted model forecasts do not encompass the unrestricted model forecasts. Similar to the *MSE-F* statistic, the limiting distribution of the *ENC-NEW* statistic is non-standard and pivotal for $k = 1$ and is non-standard and non-pivotal for $k > 1$ (Clark and McCracken (2004)) when comparing forecasts from nested models. As suggested by Clark and McCracken (2004), here again we base our inferences on a bootstrap procedure.

The bootstrap procedure: Following Rapach *et al.* (2005), we now describe the bootstrap procedure which is similar to those by Nelson and Kim (1993), Mark (1995), Kothari and Shanken (1997) and Kilian (1999). We postulate that the data are generated by the following system under the null hypothesis of no predictability:

$$y_t = a_0 + a_1 y_{t-1} + \varepsilon_{1,t} \tag{4}$$

$$z_t = b_0 + b_1 z_{t-1} + ... + b_q z_{t-q} + \varepsilon_{2,t} \tag{5}$$

where the disturbance vector $\varepsilon_t = (\varepsilon_{1,t}, \varepsilon_{2,t})'$ is independently and identically distributed with covariance matrix Σ. First, (4) and (5) are estimated by the OLS procedure with lag order q in (5) selected using the Akaike's information criterion (AIC), and the OLS residuals $\{\hat{\varepsilon}_t = (\hat{\varepsilon}_{1,t}, \hat{\varepsilon}_{2,t})'\}_{t=1}^{T-q}$ are computed. In order to generate a series of disturbances for our pseudo-sample, we randomly draw (with replacement) *T*+100 times from the OLS residuals $\{\hat{\varepsilon}_t\}_{t=1}^{T-q}$, giving us a pseudo-series of disturbance terms $\{\hat{\varepsilon}_t *\}_{t=1}^{T+100}$. Drawings of the OLS residuals are made in tandem and the contemporaneous correlation between the disturbances of the original sample is maintained. Using the OLS estimates of the parameters in equations (4) and (5) and $\{\hat{\varepsilon}_t *\}_{t=1}^{T+100}$ and setting the initial observations of y_{t-1} and $z_{t-1}, z_{t-2}, ..., z_{t-q}$ equal to zero in equations (4) and (5), we can build up a pseudo-sample of *T*+100 observations for y_t and z_t, $\{y_t *, z_t *\}_{t=1}^{T+100}$. The first 100 transient start-up observations are dropped in order to randomize the initial observations. For this pseudo-sample, we calculate the *t*-statistic corresponding to β in the in-sample predictive regression model given in (1) and the two out-of-sample statistics given in (2) and (3). This process is repeated 1000 times, giving us empirical distribution for the in-sample *t*-statistic and the out-of-sample statistics. For each statistic, the *p*-value is the proportion of the bootstrapped statistics that are greater than the statistic computed using the original sample. As both the out-of-sample tests are one sided (upper-tail), an out-of-sample statistic is significant at, say, 10% level, if the *p*-value is less than or equal to 0.10 while for the in-sample *t*-test which is two-sided, the statistic is significant at 10 % if the *p*-value is less than or equal to 0.05 or greater than or equal to 0.95.

2.2 Data mining

It is now well-recognized that data-mining becomes a concern while testing the predictive ability of multiple variables. Lo and MacKinlay (1990) and Foster *et al.* (1997) have pointed out this with respect to in-sample tests of predictability. Data mining is considered to be a serious problem for in-sample tests of predictability, and the conventional wisdom holds that out-of-sample tests are better able to guard against data mining. In our study, we have used the same data-mining environment as considered by Inoue and Kilian (2003). Suppose there are *M* different macro variables $z_{j,t}, j = 1,....M$, in turn as candidate predictors in the predictive regression model (1). Inoue and Kilian (2003) have specified the null hypothesis as $H_0 : \beta_j = 0 \ \ \forall \ j$ and the alternative hypothesis as $H_1 : \beta_j \neq 0$ for some *j*, where β_j is the coefficient corresponding to $z_{j,t}$ in (1). For an in-sample test statistic, we use $\max_{j \in \{1,...M\}} | t_{\hat{\beta}_j} |$ where $t_{\hat{\beta}_j}$ is the *t*-statistic corresponding to β_j. For the out-of-sample test statistic, we use the maximal *MSE-F* and maximal *MSE-NEW* statistics. Inoue and Kilian (2003) have derived the asymptotic distribution for the maximal in-sample and out-of-sample statistics under the null hypothesis of no predictability as well as under the local alternatives in this data mining environment. Since the limiting distributions are generally data dependent, Inoue and Kilian (2003) have recommended bootstrap procedures.

The bootstrap procedure discussed earlier is modified a little to take account for data mining problem. For *M* different macro variables $z_{j,t}, j = 1,....,M$, serving as candidate predictors for the candidate predictive regression model (1), equation (5) is augmented as follows to consider all the *M* candidate predictors

$$
\begin{aligned}
z_{1,t} &= b_{1,0} + b_{1,1} z_{1,t-1} + ... + b_{1,q_1} z_{1,t-q_1} + \varepsilon_{1,2,t} \\
&. \\
&. \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad (6) \\
z_{M,t} &= b_{M,0} + b_{M,1} z_{M,t-1} + ... + b_{M,q_M} z_{M,t-q_M} + \varepsilon_{M,2,t}
\end{aligned}
$$

where the disturbance vector $\varepsilon_t = (\varepsilon_{1,t}, \varepsilon_{1,2,t},..., \varepsilon_{M,2,t})'$ is independently and identically distributed with covariance matrix Σ. Using the system defined by (4) and (6), we proceed in a way which is similar to the bootstrap procedure described earlier to generate 1000 pseudo-samples of observations for y_t and $z_{1,t}, z_{2,t},....., z_{M,t}$ under the null hypothesis of no predictability, with each pseudo-sample matching the original sample-size. For each pseudo-sample, we calculate the t-statistic corresponding to β_j in the in-sample predictive regression model and the two out-of-sample statistics for each of the $z_{j,t}*$ variables (j=1, …, M) in turn. We then compute and store the largest and the smallest t-statistics as well as the maximal *MSE-F* and *ENC-NEW* statistics. After ordering the empirical distribution for each maximal out-of-sample statistics, the 900th , 950th and 970th values serve as the 10%, 5% and 1% critical values for each maximal out-of-sample statistics, respectively. For the in-sample t-statistic, the 950th, 975th and 995th values of the empirical distribution for the largest t-statistic serve as the 10%, 5% and 1% upper tail critical values, respectively for $\max_{j \in \{1,...,M\}} \left| t_{\hat{\beta}_j} \right|$ statistic.

2.3 General-to-specific approach

Along with analyzing each macro variable in turn, we have also employed the general-to-specific approach of model selection, as used by Clark (2004), to identify the relevant predictor macro variables. In this, we again use the predictive regression model defined in (1) but including all the variables,

$$y_{t+1}^k = \alpha + \beta_1 z_{1,t} + ... + \beta_M z_{M,t} + \gamma y_t + u_{t+1}^k \quad . \tag{7}$$

This model is estimated using data from the in-sample portion of the total sample. Each of the t-statistics corresponding to the $z_{j,t}$, t=1,…,M, variables in (7) are examined and if the smallest t-statistic (in absolute value) is greater than or equal to 1.645, we select the model that includes all M of the $z_{j,t}$ variables. If the smallest t-statistic is less than 1.645, we exclude the $z_{j,t}$ variable corresponding to the smallest t-statistic in the next model we consider. We proceed in this way and include only those values of $z_{j,t}$ variables which have significant t-statistics. If this exercise based on data from the in-sample period includes at least one of the $z_{j,t}$ variables, we then compare the out-of-sample return forecasts generated by the selected model to the out-of-sample forecasts generated by the benchmark model. We again form out-of-sample forecasts recursively and compare out-of-sample forecasts from the competing models using the *MSE-F* and *ENC-NEW* statistics. We generate *p*-values for the out-of-sample statistics by slightly modifying the bootstrap procedure described earlier. Here we generate a pseudo-sample of data for y_t and all of the $z_{j,t}$ variables under the null hypothesis that none of the $z_{j,t}$ variables is useful in predicting return. Using the pseudo-sample, we use the general-to-specific model selection procedure over the in-sample period in order to select the 'best' forecasting model, and if the selected model includes any of the $z_{j,t}$ variables, we calculate the out-of-sample *MSE-F* and *ENC-NEW* statistics. We repeat this process until we have empirical distributions of 1000 bootstrap statistics for both the out-of-sample statistics. For each out-of-sample statistic, the *p*-value is the proportion of bootstrapped statistics that are greater than the statistic computed using the original sample.

To sum up this methodology, what we do first is to use the above two methods *viz.*, the one based on each macro variable in turn- called the specific-to-general and the general-to-specific method, then determine the set of variables which have significant roles in the predictability of exchange rate, and finally check for the data mining problem to decide on the variables which appear to be important in modelling exchange rate return.

2.4 The final model

Now, it is not just enough from the point of view of modelling that we have been able to choose a set of relevant macro variables which have significant predictive ability for exchange rate return, and hence we need to check whether the macro variables thus obtained are adequate from the point of view of appropriate specification of the underlying relationship involving exchange rate return and the chosen macro variables. To that end, we need to account for serial correlation by considering appropriate lags of exchange rate return and also for any seasonal behavior in the series by including appropriate dummy variables. Taking all these into consideration, we finally propose the following specification, in the framework of a single-equation linear dynamic model, for the return on India's monthly exchange rate series:

$$y_t = \sum_{k=1}^{p} \phi_k y_{t-k} + \sum_{j=1}^{d} \xi_j D_{j,t} + \sum_{j=1}^{\widetilde{M}} \sum_{k=0}^{l} \beta_{jk} z_{j,t-k} + \varepsilon_t, \quad t = 1,2,......,T \tag{8}$$

where y_t is the difference of log of exchange rate, D_j's $(j = 1,2,...,d)$ denote the seasonal 0-1 dummies, p is the appropriate lag value of y_t capturing its autocorrelations and $z_{j,t-k} (j = 1,...,\widetilde{M}; k = 0,...,l)$ are the $\widetilde{M}, \widetilde{M} \le M$, independent macro variables having the current value as well as lags upto *l*, which have been identified to play significant roles in the prediction of exchange rate. We can write the equation compactly, in matrix notation, as

$$y_t = x_t' \gamma + \varepsilon_t \tag{9}$$

where $x_t' = (y_{t-1},..., y_{t-p}, D_{1t},..., D_{dt}, z_{1,t},..., z_{1,t-l},..., z_{\widetilde{M},t},..., z_{\widetilde{M},t-l})$ and $\gamma' = (\phi_1,...,\phi_p, \xi_1,...,\xi_d, \beta_{10},...,\beta_{1l},...,\beta_{\widetilde{M}0},...,\beta_{\widetilde{M}l})$.

Once the model has thus been specified, we carry out test for parameter instability or structural break, as it is often called, in the conditional mean function. This is done by following the approach by Andrews (2000). If the findings of this test suggest presence of one or more structural breaks, the sample is then split at the break date estimate(s) (*cf.* Bai (1994,1997a), and further analysis continues on the subsamples, provided the number of observations in each subsample is adequate; otherwise, dummy variables representing breaks are included in (9) and the analysis continues with this model.

To ensure that the conditional mean is appropriately specified, we next test, based on recursive residuals, for any remaining misspecification in the conditional mean. It is noteworthy that apart from omission of variables, any remaining misspecification of the conditional mean may be because of nonlinear dependence and this nonlinearity may be approximated by functions of the recursive residuals. As demonstrated by Kianifard and Swallow (1996), Lumsdaine and Ng (1999) and others, the use of recursive residuals, rather than the standard least squares residuals, increases the power of the tests for model misspecification. The test of misspecification applied here refers to in Lumsdaine and Ng (1999). This test envisages augmenting the specification in (9) as $y_t = x_t{}' \gamma + g(\hat{w}_{t-1)} + v_t$, where $g(\hat{w}_{t-1})$ is a (possibly nonlinear) function of the recursive residuals $\hat{w}_{t-1}$. The role of $g(\hat{w}_{t-1})$ is to orthogonalize ε_t in (9) so that the conditional mean of the resulting regression error v_t shrinks to zero. Insofar as the choice of $g(\hat{w}_{t-1})$ is concerned, a suitable candidate is $g(\hat{w}_{t-1}) = \sum_{i=1}^{s} \delta_i \hat{w}_{t-1}^{i}$ for a series expansion of length s in $\hat{w}_{t-1}$. If one or more of the δ -coefficients turn out to be statistically significant, we retain the corresponding terms in the conditional mean specification of y_t so that there is no inadequacy in specification.

Finally, we perform the Lagrange multiplier / Rao's Score test for detecting second-order dependence in the residuals, as specified by the (G)ARCH model for the errors, and the BDS test (see Brock *et al.* (1996), for details) for detecting other higher-order dependences. In the set-up of BDS test, the null hypothesis states that the underlying random variables (here the errors) are independently and identically distributed (*i.i.d.*) and the alternative includes serial correlation, higher-order dependence specified by GARCH, and other unspecified nonlinear dependences. The BDS test statistic measures the statistical significance of the correlation dimension calculations, and its computation involves choosing values of two parameters, $\tilde{\xi}$ and $\tilde{m}$, where $\tilde{\xi}$ is the radius of the hypersphere, which determines whether two points are 'close' or not and $\tilde{m}$ represents the value of the embedding dimension. As suggested by Hsieh (1991), Sewell *et al.* (1993) and Brock *et al.* (1996), in most cases, the values of $\tilde{\xi}$ used are 0.5σ and σ, where σ represents the standard deviation of the linearly filtered data, and the value of $\tilde{m}$ is set in line with the number of observations (e.g. , using only $\tilde{m} \leq 5$ if $T \leq 500$).

3 The data

This study has been carried out with data at the level of monthly frequency. The choice of this frequency has been dictated by the fact that, in India, data on macrovariables are not available at any other higher frequency. The time series of exchange rate here refers to the time series of spot Indian rupee / US dollar exchange rate, and the return on exchange rate, as defined in the preceding sections, is the first difference of logarithmic values of the spot exchange rate series. The time period considered for this study covers the period from November, 1994 to March, 2005. Thus, there are a total of 124 observations in the sample. While in all relevant computations all the 124 observations have been used, in case of computations involving out-of-sample forecasting and *MSE-F* and *ENC-NEW* test --statistics, the first 74 observations have been used as in-sample observations and the rest kept as hold-out sample. Beginning with November, 1994, the in-sample period, therefore, ends in January, 2001 and the out-of-sample period begins in February, 2001 and ends in March, 2005. The usual descriptive statistics like the mean, standard deviation, skewness and kurtosis values of return as well as of all the macro variables (at stationary values) along with the values of ADF test statistic (at level) values for unit root tests on these variables are given in Table 1.

In order to analyze the ability of each macro variable, in turn, in predicting Indian exchange rate return, we need to have, to start with, a set of relevant macro variables. To that end, we consider the following set of 25 macro variables which have been found to influence exchange rate prediction in studies concerning developed countries and which are also mentioned in theories on exchange rate. From the definitions of these variables, it is evident that some of these variables are broadly similar in nature. The characterizations of these variables in terms of stationarity[2] and seasonality are stated below.

[2] As noted below (and also evident from Table 1) that except for three macro variables *viz*., GFD, SPUSD and OMO, all other series have unit roots and their first difference / logarithmic difference values are stationary. For the sake of convenience, while discussing the results, we may not always mention 'growth /

- Bombay Stock Exchange Sensitivity Index (BSESENSEX): The Bombay Stock Exchange is the oldest stock market not only in the country but also in Asia. Established in 1857, it obtained a permanent recognition from Government of India under the Securities Contracts Act, 1956[3]. Its most important and widely-used index, called the BSESENSEX, is recognized worldwide. Since the monthly BSESENSEX series exhibits seasonality, we have applied Proc-X11 to deseasonalize this series. Thereafter, the ADF unit root test has been performed and the conclusion is that the deseasonalized series has a unit root. We have then taken the first difference in logarithm values, which is called the return on BSESENSEX, and then carried out the ADF test once again to conclude that the return series is now stationary. (Data source:www.bseindia.com)
- Call Money Rate (CMR): We use the call money rate which is the rate at which the commercial banks borrow money from other banks. This variable can be viewed as the short-term interest rate in India. The series exhibits no seasonality. However, application of the ADF test showed that it has a unit root. Accordingly, the differenced series which is found to be stationary, has been considered for the analysis. (Data source: www.rbi.org.in)
- M0: This variable is a component of the stock of money, basically defined as the reserve money. This series shows no seasonality and hence no seasonal adjustment is done. The ADF test for unit root showed that it is nonstationary and hence the first difference of its logarithmic values has been used. The series thus obtained may be called the reserve money growth, and this series has been found to be stationary. (Data source: www.rbi.org.in)

change' in respect of these latter variables; we may merely state the names of the variables although these would refer to their growths or changes, as the case may be.

[3] Earlier it was an Association of Persons (AOP), but now it is a demutualised and corporatised entity according to Companies Act, 1956, pursuant to BSE (Corporatisation and Demutualisation) Scheme, 2005, notified by the Securities and Exchange Board of India (SEBI).

- M1: Defined as the *narrow money,* this important variable has been used in many similar works to study the relationship between exchange rate and money supply. Since the series shows seasonality, we have adjusted this series for seasonality and then used the stationary series of the first difference of its logarithmic values for analysis. The variable thus may be called the narrow money growth. (Data source: www.rbi.org.in)
- M3: *Broad money* or M3 series needed seasonal adjustment. Thereafter, the first difference of the logarithmic values of this deseasonalized series has been considered to make it stationary. This variable thus may be called the broad money growth. (Data source: www.rbi.org.in)
- Consumer price index (CPI): The price level with base 1984-85=100 has been found to be nonstationary; so we have taken the first difference in logarithmic values of the series. This differenced series is usually known as inflation rate. (Data source: www.rbi.org.in)
- Wholesale price index (WPI): The price level with base 1984-85=100 is nonstationary while its first difference in logarithmic values is stationary. (Data source: www.rbi.org.in)
- Foreign currency asset (FCA): The foreign currency asset comprises foreign securities held in the issue department and balances held abroad along with investments in foreign securities held in the banking department. It is, in fact, a component of foreign exchange reserve. Since it has been found to be nonstationary, we have carried out our analysis with the stationary series obtained as first difference in logarithmic values. (Data source: www.rbi.org.in)
- Total reserve of foreign exchange (TR): This series has been found to be seasonal and hence it has been seasonally adjusted. The adjusted series has shown the presence of a unit root and accordingly its first difference at log-level has been taken for the purpose of our analysis. As shown in Table 1, the resulting series is stationary. (Data source: www.rbi.org.in)

- Industrial production (IP): The industrial production index with base 1993-1994=100 has been found to be highly seasonal and hence it has been adjusted for seasonality. Thereafter, we have taken the first difference in the log values of this index and this has been found to be stationary. This adjusted series may be called the growth in industrial production. (Data source: www.rbi.org.in)
- Export (EX): This variable is an important component of trade. This variable includes transfer of the ownership of goods from residents of a country to non-residents and services provided by resident producers of the country to non-residents. Since this series was found to be nonstationary, we have considered the first difference of the log values to achieve stationarity. (Data source: www.rbi.org.in)
- Import (IM): We have considered the first difference of the log-levels of India's import so as to obtain a stationary series, and the resulting variable is import growth. Being a component of trade this variable is expected to be important for exchange rate predictability. (Data source: www.rbi.org.in)
- Trade balance (TB): This macro variable being the difference between exports and imports, is important for studying predictability of exchange rate. However, it is nonstationary and hence the first difference of the level values has been taken to achieve stationarity. The variable thus obtained is called the change in trade balance. (Data source: www.rbi.org.in)
- Gross fiscal deficit (GFD): This series was seasonally adjusted and the adjusted series has been found to be stationary. Thus, no differencing was required to be done to achieve stationarity for this series. (Data source: www.rbi.org.in)
- Sale/Purchase of US dollar (SPUSD): We have used the series without any seasonal adjustment as well as differencing, since it has been found to be stationary in the level values having no significant seasonality. (Data source: www.rbi.org.in)
- Open market operations (OMO): Open market operations by the Reserve Bank of India are confined to the purchase and sale of Government securities and treasury bills. The government might resort to this to sterilize the effects of intervention. We

have considered the unadjusted level values of this macro variable for our analysis since it is a stationary series having no significant month effect. (Data source: www.rbi.org.in)

- Federal funds rate (FFR): The series has been considered at the first difference of its level values and this ensures stationarity. This, in fact, is the short term US interest rate. (Data source: www.federalreserve.gov)
- Six-month treasury bill rate of US (TBRU6): We have taken the first difference of this rate for our study as the series was found to be nonstationary. (Data source: www.federalreserve.gov)
- Three-month treasury bill rate of US (TBRU3): For this rate also, we have considered the first difference of its level values and thus achieved stationarity. (Data source: www.federalreserve.gov)
- NASDAQ: We have taken the monthly closing values of the NASDAQ composite index which is an important stock price index of the USA. This series was, however, found to be nonstationary and hence we have taken the first difference of the logarithms of this series to make it stationary. (Data source: www.finance.yahoo.com)
- World gold price (WGP): We have considered the A.M. fix of the London Gold Market, i.e., the price of gold in US dollar per troy oz fixed at 10:30 A.M. London local time by a group of select commercial banks constituting the London Gold Market Fixing Limited. The US dollar per troy oz is converted into rupees per troy oz of gold using the nominal exchange rate. Since the series was found to be nonstationary, we have used the first difference of its logarithmic values for our analysis. (Data source: thebulliondesk.com)
- Foreign direct investment (FDI): Foreign direct investment in India includes direct investment by non-residents and disinvestments of equity capital. The series is nonstationary; so we have taken the difference of log-level values for this variable. (Data source: www.rbi.org.in)

- Foreign institutional investment (FII): This represents the inflow of funds by foreign institutional investors. Since the ADF test suggests that this variable has a unit root, we have considered its first difference to achieve a stationary series. (Data source: www.rbi.org.in)
- Total foreign investment (FINV): This variable is, by definition, the sum of foreign direct investment and portfolio investment. As already mentioned, foreign investment in India include direct investment by non-residents and disinvestments of equity capital. Portfolio investment relates to purchase and sale of equity and debt securities usually traded in financial market. Major components of such investment include FIIs' investment, funds raised through GDRs /ADRs by Indian companies and through offshore funds. This macro variable might have an important role in the predictability of exchange rate. The series was found to be nonstationary and hence we have taken the first difference of this series to make it stationary. (Data source: www.rbi.org.in)

Other than these variables, there are two other relevant variables *viz.*, treasury bill rate of India and repo rates (as discussed in Section 1) which could not be included in our analysis, since the time series of these two variables are available from a much later period than considered by us in this study i.e., from the years 1999 and 2000, respectively. All the computations were done using GAUSS package and codes provided by Rapach and Wohar (2005) (http://pages.slu.edu/faculty/rapachde/Research.htm).

Table 1

Descriptive statistics of the macroeconomic variables and results of unit root test

Variable	Mean	Standard deviation	Skewness	Kurtosis	ADF test statistic value	Critical value
EXRATE	0.002843	0.012865	1.455054	10.87957	-2.798771	-3.4839
BSE	0.002725	0.065032	-0.159991	2.955874	-1.804911	-4.0355
CMR	-0.029435	4.175531	-0.473210	15.47537	-3.211494	-4.0361
M0	0.008855	0.015595	0.187930	4.050973	-2.538960	-4.0348
M1	0.010398	0.010071	0.189329	4.441182	-1.728017	-4.0355
M3	0.012318	0.006207	1.005136	7.774536	-1.249168	-3.4843
CPI	0.004925	0.006749	1.513375	8.997051	-2.776162	-3.4847
WPI	0.004174	0.004398	0.779577	3.906735	-3.639175	-4.0348
FCA	0.018200	0.024129	0.129937	5.337466	-2.493902	-4.0342
TR	0.017037	0.021772	0.297738	5.299159	-1.982519	-4.0342
IP	0.005268	0.021772	0.297738	5.299159	-2.518701	-4.0348
EX	0.012177	0.074991	0.432297	4.355001	-2.649396	-4.0355

Note: Descriptive statistics are given for the stationary series of macroeconomic variables (including return on India's foreign exchange rate, denoted as EXRATE) used in the analysis.
** indicates that the concerned time series is stationary at level values. The ADF test statistic is obtained for the level values of all the variables. The estimating equation for the ADF test has both an intercept and linear trend term.*
The last column shows MacKinnon 1% critical values for rejection of hypothesis of a unit root.

Table 1 (Contd.)

Variables	Mean	Standard deviation	Skewness	Kurtosis	ADF test statistic value	Critical value
IM	0.013949	0.077014	-0.123651	2.718241	-2.545445	-4.0355
TB	-67.41158	1539.164	-0.045104	3.344025	-1.963985	-3.4843
GFD*	8960.139	5457.359	2.823618	18.85321	-7.344202*	-4.0355
SPUSD*	3137.686	5702.051	1.666698	7.969149	-4.176175*	-3.4843
OMO*	-1858.859	3146.882	-1.715684	5.566018	-3.755472*	-3.4852
FFR	-0.021452	0.176836	-1.178854	5.118306	-1.093513	-2.5825
TBUS6	-0.021935	0.190846	-0.847477	5.218031	-1.128894	-2.5827
TBUS3	-0.020565	0.186016	-1.221140	5.860363	-1.327914	-2.5824
NASDAQ	0.007903	0.083512	-0.683903	3.924829	-2.094944	-3.4839
WGP	0.003447	0.030464	0.836628	7.560381	1.629390	-2.5825
DI	0.004942	0.542500	0.126978	3.776005	-1.027511	-2.5827
FII	11.42742	467.4723	1.126644	15.42623	-3.332489	-3.4852
FINV	13.87903	518.5149	0.980891	11.94189	-2.969336	-3.4852

Note: Descriptive statistics are given for the stationary series of macroeconomic variables used in the analysis.
** indicates that the concerned time series is stationary at level values. The ADF test statistic is obtained for the level values of all the variables. The estimating equation for the ADF test has both an intercept and linear trend term.*
The last column shows MacKinnon 1% critical values for rejection of hypothesis of a unit root.

4 Empirical Results

4.1 Selection of macro variables

In this section, we first report the results of specific-to-general approach to macro variable selection using predictive regression. Now, it is quite evident from the description of the macro variables in the preceding section, that some of the variables are similar in nature. Some others are sum of two or more variables. Since this approach uses one variable at a time, it is quite meaningful if the initial choice is done from a larger set. Hence in this approach we have tried with all these variables- one at a time, and finally identified only those macro variables which have significant roles in predicting the return on India's exchange rate. On the other hand, while applying the general-to-specific approach, we have eliminated some such similar variables based on the *p*-values of in-sample predictive regression models obtained in the first approach.

Table 2 presents the in-sample regression results for the predictive regression in (1) for each of the macro variables in turn. This table also reports the values of Theil's *U* and the *MSE-F* and *ENC-NEW* statistics for the out-of-sample forecasts. For our computations, we have considered the horizons of 1, 3, 12 and 24 months.

We now describe briefly the results reported in Table 2 to examine the role of each variable in predictability of exchange rate return. Looking at the results for the first macro variable in our set *viz*., BSESENSEX, we find that none of the criteria- be it in-sample *t*-statistic value or *MSE-F* and *ENC-NEW* test statistics based on out-of-sample forecasting values- shows that this macro variable has no predicting ability for return on exchange rate since none of the test statistic value is significant for any of the four horizons. Even the value of Theil's *U* which is a descriptive measure, has a value greater than 1 for all the horizons indicating that the restricted model forecast RMSE has a smaller value than that of the unrestricted one. As regards call money rate (CMR), the in-sample *t*-statistic value is significant for the 1- and 12-month horizons. But none of the out-of-sample statistics is significant for this variable. Also, the Theil's *U* value is less than 1 for k = 3 and 12. Thus, we may infer that CMR has some significant role in predicting the return on India's exchange rate. For reserve money or M0 as it is called, we find that the in-sample *t*-statistic is significant at 5 per cent level of significance for k=1 only and none of the out-of-sample statistics is significant. Thus, the statistical evidence for predictive ability of M0 is not very strong. None of the other money supply variables *viz*., M1 and M3 exhibit significance in terms of either in-sample *t*-statistic or out-of-sample *MSE-F* and *ENC-NEW* statistics. The results are similarly surprising for the price indices, CPI and WPI, which also show no significance in terms of any of the test statistics considered in this study. The in-sample *t*-statistic as well as the out-of-sample *MSE-F* and *ENC-NEW* statistics are significant for foreign currency asset (FCA) at 3-month horizon. The results are similar for total reserve (TR) where the in-sample *t* as well as the out-of-sample *MSE-F* and *ENC-NEW* statistics are significant at 3-month horizon while only the *MSE-F* statistic is significant at 1-month horizon. Also the Theil's *U*-measure yields a value which is less than 1 at horizons 1, 3 and 12. Note that FCA is a component of TR and hence we should include only one of them in our full model. Comparing the findings on these two macro variables, it is quite evident that TR has somewhat better predictive ability for return than FCA, and accordingly between these two variables, we choose TR for further analysis. As regards the last three macro variables which pertain to foreign investment *viz*., foreign direct investment (FDI), foreign institutional investment (FII) and total foreign investment (FINV), we find that while FDI has no predictive ability, FII and FINV seem to have some significant roles since the in-sample *t*-statistic value has been found to be significant for both these macro variables. However, these two macro variables are obviously of similar nature, and hence as in the case of choice between TR and FCA, we have chosen FINV instead of FII primarily because the *p*-value corresponding to the *t*-statistic is much smaller as compared to that for FII, and also for the fact that FINV is more representative of the foreign investment in a country while FII is a component of FINV.

Insofar as the findings on predictive regression for each of industrial production, export, import and trade balance are concerned, we can conclude from the values of both the in-sample and out-of-sample forecasting test statistics that none of these have any significant predictive ability for any of the four horizons. We observe from Table 2 that the macro variable GFD has many significant test statistic values. While the in-sample *t*-statistic and the out-of-sample *MSE-F* statistic for this variable are significant for the 12 as well as 24- month horizons, the *ENC-NEW* statistic is significant for the 3, 12 and 24-

month horizons. These results clearly establish the importance of this variable in predicting exchange rate return. Sale/purchase of US dollars (SPUSD) as well as open market operations (OMO) are found to have some of their test statistic values significant. For SPUSD, the in-sample *t*-statistic is significant for the 12-month horizon and the *ENC-NEW* statistic is significant for the 3-month horizon at 6 per cent level of significance only. As for OMO, the in-sample *t* and out-of-sample *MSE-F* and *ENC-NEW* statistics are found to be significant for the 12 and 24-month horizons. Although each of these two variables has been found to have significant predictive ability for return on exchange rate, it may be noted that both are essentially in the nature of effects of intervention by the RBI in the foreign exchange market. As expectedly, they have also been found to be highly correlated. Hence, both should not be included in the final model for returns on exchange rate, and accordingly we have considered SPUSD only for the subsequent analysis. All the three interest rates of the US *viz*., Federal funds rate (FFR), six month US treasury bill rate (TBRU6) and three month US treasury bill rate (TBRU3) have been found to have some significant in-sample *t*-statistic values. While the FFR has significant 24-month horizon *t*-statistic, the 3-month and 6-month US treasury bill rates have significant in-sample *t*-statistics for the 12 as well as 24 –month horizons. However, none of *MSE-F* and *ENC-NEW* forecasting test statistics has been found to be significant for any of these three variables. Our empirical findings on NASDAQ suggest that the US stock market does have some influence on the Indian exchange rate return as exhibited by the in-sample *t*-statistic value which is found to be

Table 2

In-sample and out-of-sample predictability test results

Horizon (month)	1	3	12	24	1	3	12	24
	BSESENSEX				Call Money Rate (CMR)			
$\hat{\beta}$	0.000935	0.000545	-0.000202	0.005979	-0.001569	0.000696	0.003228	-0.000790
t-statistic	0.773212 [0.208]	0.286482 [0.396]	-0.036301 [0.520]	1.151283 [0.220]	**-1.356089 [0.087]**	0.372293 [0.359]	**1.838157 [0.042]**	-0.300087 [0.533]
R^2	0.030955	0.020937	0.018084	0.000624	0.040826	0.021288	0.021632	0.001627
Theil's U	1.017502	1.017055	1.001503	1.0000757	1.004854	0.999321	0.997979	1.001551
MSE-F	-1.671170 [0.871]	-1.563083 [0.840]	-0.114004 [0.410]	-0.003935 [0.426]	-0.472292 [0.546]	0.063898 [0.238]	0.154079 [0.133]	-0.080486 [0.624]
ENC-NEW	-0.510228 [0.856]	-0.596818 [0.873]	-0.055035 [0.526]	-0.001268 [0.520]	-0.224068 [0.684]	0.032207 [0.360]	0.077323 [0.207]	-0.040152 [0.697]
	M0				M1			
$\hat{\beta}$	-0.001991	-0.002843	0.0008825	-0.001201	0.000594	-0.000729	0.000372	0.004051
t-statistic	**-1.722309 [0.045]**	-1.357130 [0.902]	0.227650 [0.397]	-0.397368 [0.590]	0.505872 [0.274]	-0.403508 [0.637]	0.107476 [0.428]	0.969883 [0.162]
R^2	0.0496198	0.033877	0.018326	0.001742	0.028199	0.021351	0.018104	0.003063
Theil's U	1.014914	0.996439	1.002269	1.002127	1.022462	1.00360	1.003266	1.001468
MSE-F	-1.429521 [0.834]	0.336437 [0.146]	-0.171839 [0.558]	-0.110232 [0.566]	-2.129303 [0.915]	-0.336915 [0.591]	-0.247012 [0.709]	-0.076203 [0.547]
ENC-NEW	0.186367 [0.270]	0.384658 [0.150]	-0.063243 [0.621]	-0.048708 [0.633]	-0.745720 [0.923]	-0.151423 [0.688]	-0.099846 [0.763]	-0.036541 [0.618]
	M3				Consumer Price Index (CPI)			
$\hat{\beta}$	0.000757	0.002602	0.002067	0.005022	0.000307	0.001323	0.006731	0.012601
t-statistic	0.654876 [0.228]	1.300604 [0.127]	0.428082 [0.363]	0.885690 [0.282]	0.264215 [0.395]	0.633327 [0.327]	1.093769 [0.193]	1.075454 [0.239]
R^2	0.029595	0.031876	0.019430	0.005243	0.026693	0.023384	0.033125	0.026760
Theil's U	1.012283	0.991505	1.005321	1.007548	1.001052	0.997992	0.992734	1.003059
MSE-F	-1.176996 [0.793]	0.808797 [0.077]	-0.401195 [0.613]	-0.388101 [0.680]	-0.102955 [0.317]	0.189363 [0.235]	0.558285 [0.184]	-0.158340 [0.503]
ENC-NEW	-0.400089 [0.811]	0.444650 [0.156]	-0.173093 [0.683]	-0.18786 [0.762]	-0.047127 [0.447]	0.109720 [0.368]	0.290219 [0.277]	-0..078313 [0.600]

Note: Bold entries indicate statistical significance. Figures in parentheses show the p-values.

Table 2 (Contd.)

Horizon	1	3	12	24	1	3	12	24
	Wholesale Price Index (WPI)				Foreign Currency Asset (FCA)			
$\hat{\beta}$	-0.000974	-0.002436	0.003419	0.0091119	-0.000776	-0.005507	-0.009003	-0.011389
t-statistic	-0.837116 [0.805]	-1.276392 [0.891]	0.470163 [0.368]	1.030508 [0.256]	-0.666015 [0.751]	**-2.162986 [0.032]**	-1.169428 [0.833]	-0.861398 [0.736]
R^2	0.031781	0.030289	0.021727	0.013000	0.0297135	0.069880	0.043240	0.020054
Theil's U	0.994889	0.997901	1.004141	0.998073	0.998014	0.968889	1.003351	1.029875
MSE-F	0.504734 [0.130]	0.1979310 [0.212]	-0.312740 [0.493]	0.100493 [0.343]	0.195218 [0.194]	**3.066709 [0.015]**	-0.253376 [0.493]	-1.486547 [0.840]
ENC-NEW	0.3114821 [0.199]	0.137634 [0.306]	-0.064035 [0.515]	0.0507521 [0.430]	0.181410 [0.257]	**2.273341 [0.025]**	-0.093537 [0.579]	-0.717124 [0.904]
	Total Reserve (TR)				Industrial Production (IP)			
$\hat{\beta}$	-0.001244	-0.006455	-0.012166	-0.018222	-0.000188	-0.001797	0.001984	0.002700
t-statistic	-1.068408 [0.856]	**-2.599236 [0.008]**	-1.644187 [0.888]	-1.292894 [0.813]	-0.157249 [0.562]	-1.046036 [0.864]	0.920186 [0.247]	1.108117 [0.220]
R^2	0.035303	0.087602	0.063215	0.046827	0.026328	0.0255538	0.019239	0.0025547
Theil's U	0.988272	0.953714	0.995197	1.032066	1.003155	0.9960045	1.002489	1.000407
MSE-F	**1.169878 [0.062]**	**4.672767 [0.003]**	0.367641 [0.192]	-1.59055 [0.875]	-0.307715 [0.423]	0.377838 [0.106]	-0.188478 [0.629]	-0.021144 [0.432]
ENC-NEW	0.801040 [0.104]	**3.574235 [0.003]**	0.256217 [0.255]	-0.770604 [0.934]	-0.143759 [0.553]	0.204079 [0.190]	-0.080930 [0.708]	-0.010509 [0.528]
	FINV				Export (EX)			
$\hat{\beta}$	-0.000920	-0.00208	0.000103	0.000789	-0.000882	0.000070	0.000259	0.000577
t-statistic	-0.774443 [0.786]	**-1.294212 [0.029]**	0.022957 [0.453]	0.157105 [0.397]	-0.755939 [0.782]	0.0531199 [0.471]	0.132297 [0.393]	0.176111 [0.402]
R^2	0.030970	0.025642	0.018073	0.001545	0.030742	0.020484	0.018092	0.001563
Theil's U	1.023941	0.999830	1.001489	1.002557	1.003039	1.004692	1.00003	1.006709
MSE-F	-2.264612 [0.681]	0.016009 [0.298]	-0.112940 [0.460]	-0.132472 [0.484]	-0.296483 [0.380]	-0.438002 [0.813]	-0.002194 [0.375]	-0.345366 [0.871]
ENC-NEW	-0.533029 [0.616]	0.054075 [0.437]	-0.036108 [0.546]	-0.059364 [0.560]	-0.013273 [0.377]	0.0243760 [0.529]	0.0041032 [0.441]	-0.134122 [0.878]

Note: Bold entries indicate statistical significance. Figures in parentheses show the p-values.

Table 2 (Contd.)

Horizon	1	3	12	24	1	3	12	24
	Import (IM)				Trade Balance (TB)			
$\hat{\beta}$	-0.000233	-0.000715	-0.001481	0.000376	-0.000989	0.000955	0.001752	0.000654
t-statistic	-0.200472 [0.556]	-0.605533 [0.764]	-0.74143 [0.740]	0.170796 [0.415]	-0.840305 [0.788]	0.796551 [0.206]	0.612189 [0.279]	0.256193 [0.391]
R^2	0.026453	0.021338	0.018715	0.001540	0.031824	0.021888	0.018834	0.001565
Theil's U	1.011275	0.999502	1.000835	1.000853	1.006571	1.000896	1.002451	1.003388
MSE-F	-1.086542 [0.736]	0.046865 [0.223]	-0.063375 [0.494]	-0.044315 [0.511]	-0.637650 [0.608]	-0.084092 [0.410]	-0.185592 [0.681]	-0.175268 [0.692]
ENC-NEW	-0.478653 [0.817]	0.0287776 [0.330]	-0.030650 [0.581]	-0.021285 [0.601]	-0.091346 [0.482]	0.061694 [0.320]	-0.089194 [0.778]	-0.083116 [0.762]
	Gross Fiscal Deficit (GFD)				Sale/Purchase of US dollars (SPUSD)			
$\hat{\beta}$	-0.000870	-0.002217	-0.018881	-0.068832	-0.001329	-0.003303	-0.028036	-0.045936
t-statistic	-0.744061 [0.793]	-1.095640 [0.840]	**-2.147789 [0.070]**	**-4.972827 [0.006]**	-1.091797 [0.858]	-0.831508 [0.783]	**-3.625015 [0.009]**	-1.894119 [0.859]
R^2	0.030599	0.028610	0.120965	0.348166	0.035705	0.037015	0.170643	0.121563
Theil's U	1.001047	1.019187	0.964736	0.880456	1.037694	1.061187	0.978286	1.068959
MSE-F	-0.102533 [0.276]	-0.278647 [0.415]	**2.828793 [0.044]**	**7.539640 [0.011]**	-3.495167 [0.969]	-5.263673 [0.933]	1.705625 [0.177]	-3.246327 [0.737]
ENC-NEW	0.455598 [0.160]	**1.372943 [0.050]**	**5.893898 [0.001]**	**4.228756 [0.020]**	0.790506 [0.118]	**2.621505 [0.060]**	1.671682 [0.181]	-1.493358 [0.815]
	Open Market Operations (OMO)				Federal Funds Rate (FFR)			
$\hat{\beta}$	-0.000037	0.001853	0.013548	0.028774	-0.000885	-0.002346	0.009018	0.028680
t-statistic	-0.031034 [0.494]	0.953984 [0.201]	**2.241930 [0.049]**	**2.211037 [0.096]**	-0.762443 [0.752]	-1.102336 [0.812]	1.845685 [0.119]	**6.560040 [0.003]**
R^2	0.026135	0.026086	0.077412	0.103780	0.030821	0.029533	0.042896	0.125509
Theil's U	1.012052	1.011197	0.958962	0.945911	1.006652	1.010899	0.986116	0.956095
MSE-F	-1.160062 [0.771]	-1.035061 [0.732]	**3.321946 [0.042]**	**3.058480 [0.047]**	-0.645455 [0.592]	-1.007966 [0.535]	1.077548 [0.232]	2.442703 [0.155]
ENC-NEW	-0.377621 [0.786]	0.119916 [0.333]	**2.857213 [0.039]**	**1.871340 [0.076]**	-0.113824 [0.507]	-0.358485 [0.606]	1.216078 [0.253]	1.369916 [0.225]

Note: Bold entries indicate statistical significance. Figures in parentheses show the p-values.

Table 2 (Contd.)

Horizon	1	3	12	24	1	3	12	24
	Six-month US Treasury Bill Rate (TBRU6)				Three-month US Treasury Bill Rate (TBRU3)			
$\hat{\beta}$	0.000534	-0.000076	0.0051864	0.0215734	0.0001700	-0.000884	0.0069318	0.0232380
t-statistic	0.457087 [0.331]	-0.044338 [0.503]	**1.929268** **[0.079]**	**4.680175** **[0.012]**	0.145846 [0.435]	-0.494679 [0.659]	**1.850865** **[0.098]**	**4.367199** **[0.019]**
R^2	0.027819	0.020486	0.026206	0.071188	0.026299	0.021760	0.0328200	0.0839392
Theil's U	1.008953	1.008696	0.998929	0.982207	1.008505	1.007428	0.9918420	0.978891
MSE-F	-0.865712 [0.678]	-0.806892 [0.550]	0.0814643 [0.341]	0.950510 [0.260]	-0.822985 [0.685]	-0.690514 [0.491]	0.627679 [0.259]	1.133430 [0.221]
ENC-NEW	-0.127477 [0.534]	-0.286449 [0.597]	0.064437 [0.437]	0.500377 [0.260]	-0.158301 [0.594]	-0.294949 [0.598]	0.427109 [0.345]	0.606808 [0.285]
	NASDAQ				World Gold Price (WGP)			
$\hat{\beta}$	-0.000451	0.002135	0.007929	0.016958	-0.002039	-0.002796	-0.010711	-0.023140
t-statistic	-0.38763 [0.654]	1.460971 [0.106]	**1.912645** **[0.059]**	**3.254108** **[0.019]**	**-1.778890** **[0.040]**	**-1.525339** **[0.077]**	**-1.646804** **[0.087]**	**-1.805563** **[0.099]**
R^2	0.027345	0.028095	0.0391473	0.0487248	0.051149	0.0334102	0.054802	0.074420
Theil's U	1.005749	1.004238	0.990772	1.000725	0.977228	0.988114	0.977755	0.976318
MSE-F	-0.558600 [0.578]	-0.075460 [0.285]	0.711159 [0.132]	-0.088720 [0.486]	**2.310227** **[0.022]**	**1.137521** **[0.065]**	**1.748738** **[0.017]**	**1.276631** **[0.034]**
ENC-NEW	-0.178050 [0.600]	0.236426 [0.267]	0.479706 [0.177]	-0.040773 [0.566]	**1.823196** **[0.035]**	0.640658 [0.117]	**1.049020** **[0.033]**	**0.669944** **[0.071]**
	Foreign Direct Investment (FDI)				Foreign Institutional Investment (FII)			
$\hat{\beta}$	-0.000924	-0.000130	0.000529	0.0002972	-0.000696	-0.002319	0.001043	0.000796
t-statistic	-0.798628 [0.818]	-0.097456 [0.550]	0.261895 [0.386]	0.148528 [0.466]	-0.576337 [0.737]	**-1.084165** **[0.096]**	0.192453 [0.455]	0.084527 [0.466]
R^2	0.031276	0.020505	0.018157	0.001531	0.028815	0.0262282	0.018151	0.001532
Theil's U	1.007950	1.000527	1.000373	0.998080	1.040956	1.005912	1.003355	1.007745
MSE-F	-0.769914 [0.636]	-0.495408 [0.383]	-0.028321 [0.476]	0.100111 [0.170]	-3.779966 [0.118]	-0.550819 [0.271]	-0.253710 [0.259]	-0.398094 [0.046]
ENC-NEW	-0.167774 [0.540]	-0.019167 [0.502]	-0.011547 [0.547]	0.050530 [0.237]	-1.122203 [0.673]	-0.220754 [0.620]	-0.129483 [0.511]	-0.174495 [0.568]

Note: Bold entries indicate statistical significance. Figures in parentheses show the p-values.

significant for the 12 as well as 24- month. The findings corresponding to the next macro variable *viz*., world gold price (WGP) has been found to be very significant. All the in-sample and out-of-sample test statistic values at all the four horizons except the *ENC-NEW* for 3-month horizon have been found to be significant for this macro variable. This shows that the predictability of return on exchange rate is strongly influenced by world gold price.

In order to apply the in-sample general-to-specific model selection criterion combined with tests of out-of-sample forecasting ability, we cannot obviously begin with a large model having as many as 24 macro variables. To reduce this initial set, we may note that, as already discussed, there are some variables which are similar in nature while some are components of other variables. Accordingly, we have dropped FCA, six-month and three-month US treasury bill rates, FII and OMO from the set of macro variables which were found to have significant predictive ability by the specific-to-general model selection approach, and consequently we are left with a set of nine macro variables comprising CMR, M0, TR, GFD, SPUSD, FFR, NASDAQ, WGP and FINV. Other than these, we have also included some variables which are normally argued, in economics and finance, to have important roles in determining exchange rate but which have not been found to be significant by the first approach. These, to our understanding, are BSESENSEX, M1, CPI, IP and TB. Thus, we have the following 14 macro variables for the general-to-specific approach: BSESENSEX, CMR, M0, M1, CPI, TR, IP, GFD, SPUSD, TB, FFR, NASDAQ, WGP and FINV. The empirical findings by this approach are reported in Table 3. It may be noted that the critical values for $\max_{j \in \{1,\ldots,14\}} \left| t_{\hat{\beta}_j} \right|$, maximal *MSE-F* and maximal *ENC-NEW* for all the horizons have been generated using data-mining-robust bootstrap procedure discussed earlier. The critical value computed using the bootstrap procedure for $\max_{j \in \{1,\ldots,14\}} \left| t_{\hat{\beta}_j} \right|$ for the 24- month horizon is 5.52. This is obviously less than 6.56, which is the maximum (amongst these 14 variables) value of the *t*-statistic for the 24-month horizon. Also, the critical value of *MSE-F* test statistic is 3.985, which is less than the value of 4.673 obtained for the 3-month horizon. The same is the finding with respect to the *ENC-NEW* test statistic. Thus, for all these three tests, the null hypothesis of no predictability is rejected. We can, therefore, conclude that the best evidence for in-sample and out-of-sample predictive ability, which is reflected in the maximum (amongst these 14 variables) values of the *t*-statistic as well as the *MSE-F* and *ENC-NEW* statistics, is free from any data mining problem.

Now, analysing the results presented in Table 3, we note that for the 1-month horizon, the only variable which has been found to have significant explanatory power is M0 or the reserve money growth. For the 3-month horizon also, there is only one significant macro variable, but now the variable is total reserve (TR). For 12-month horizon, the number of explanatory variables has increased to five and these are GFD, SPUSD, FFR, NASDAQ and FINV. As for the 24-month horizon, eight macro variables *viz*., CMR, M0, M1, GFD, SPUSD, FFR, WGP and FINV have been found to have predictive ability for return on India's foreign exchange rate at monthly-level frequency. Combining the findings for the four horizons, we note that the only macro variable which has been found to have significant predictive ability by this approach, but not by the earlier one, is M1, the narrow money; the other significant variables are the same by the two approaches.

Table 3

General-to-specific model selection results

Horizon (month)	1	3	12	24
Included variables	M0	TR	GFD,SPUSD,FFR, NASDAQ, FINV	CMR, M0, M1, GFD, SPUSD, FFR, WGP,FINV
Theil's U	1.014914	0.953714	0.979230	0.921188
MSE-F	-1.429521 [0.222]	4.672767 [0.023]	1.629134 [0.132]	4.639183 [0.091]
ENC-NEW	0.186367 [0.404]	3.574235 [0.085]	4.842013 [0.118]	2.772104 [0.203]

Note: Figures in parentheses indicate the p-values

Thus, based on both the methods of selection of macro variables and considering all the four horizons together, we can conclude that the relevant macroeconomic variables which have been found to have significant role in predicting India's monthly exchange rate return are ten in number and these are reserve money growth (M0), narrow money growth (M1), change in foreign exchange reserve (TR), gross fiscal deficit (GFD), sale/purchase of US dollar (SPUSD), change in Federal funds rate (FFR), US stock price return (NASDAQ), change in call money rate (CMR), rate of change in gold price (WGP) and change in total foreign investment (FINV).

4.2 The final estimated model

Once the significant macro economic variables have been chosen, we consider the dynamic linear regression model specified in (9) where we now use all the ten macro variables to obtain the 'best' model for India's monthly exchange rate return. Before we actually estimate the model, it is essential to check whether there is any structural break in the monthly exchange rate return series. We have carried out the Quandt-Andrews test for parameter stability and the relevant statistic was found to be 9.91, which is lower than the tabulated value of 10.00- thus indicating that the null hypothesis of no structural break cannot be rejected for the monthly series. The final model is, therefore, obtained using all the sample observations. For estimating this model, the number of lagged values of return, *p*, was initially taken to be a moderate value of 10 so that the autocorrelation could be entirely captured by the model, and the value of l, the lag value for the independent macro variables, was fixed at 2. Further, the number of dummy variables (*d*) was obviously taken to be 12 since the data is at monthly level. This model was estimated by using the OLS method of estimation and the estimated model is presented in equation (10) below. The estimated model having significant variables only has been obtained as follows:

$$\hat{y}_t = \underset{(1.792)^{*}}{0.153}\, y_{t-3} - \underset{(2.332)^{**}}{0.185}\, y_{t-5} - \underset{(3.537)^{***}}{(7.50\times 10^{-6})}\, FINV_t - \underset{(4.997)^{***}}{(1.08\times 10^{-6})}\, SPUSD_t$$

$$+ \underset{(4.092)^{***}}{0.209}\, TR_t - \underset{(2.827)^{***}}{0.0007}\, CMR_{t-1} - \underset{(2.056)^{**}}{(4.44\times 10^{-6})}\, FINV_{t-1} + \underset{(2.887)^{***}}{0.262}\, M1_{t-1} \tag{10}$$

*[The values in parentheses indicate corresponding absolute values of t-ratios; *, **, *** indicate significance at 10%, 5% and 1% levels of significance, respectively.]*

We note that only the third and fifth lags of exchange rate return are found to be significant. None of the monthly dummies is significant and hence we can conclude that there is no systematic month effect in foreign exchange return. The macro variables which are found to have contemporaneous dependence with exchange rate return are the change in total foreign investment (FINV), sale / purchase of US dollar (SPUSD) and the change in total reserve of foreign exchange (TR). The first lag of change in call money rate (CMR), change in FINV and narrow money growth (M1) are also found to influence exchange rate return. It is noteworthy that the macro variable, change in FINV has both contemporaneous and lagged effects on return. This shows the importance of this macro variable i.e., total foreign investment, in the determination and predictability of India's exchange rate return.

Once the model has been estimated, the usual diagnostic tests on the residuals of this estimated model were carried out. The Ljung-Box test suggested a few significant values. To be specific, the *p*-values for the first three lags were found to be 0.026, 0.083 and 0.086, indicating that while the first lag is quite highly significant , the other two *viz*., the second and third are significant only at 9 per cent level of significance. However, the Ljung-Box statistic values for the squared residuals indicate that there is no squared dependence in the series. The finding of no volatility in the monthly series is quite likely since volatility is usually manifested in financial time series of high frequency like, for instance, the daily and hourly levels. We have also carried out the test for misspecification as discussed in Section 2. By augmenting the model in (10) by including suitable polynomial functions of the recursive residuals at *t*-1 (i.e., $\hat{w}_{t-1}$) and then estimating it by OLS procedure, we have obtained the following estimated model:

$$\hat{y}_t = \underset{(1.200)}{0.104}\, y_{t-3} - \underset{(1.775)^{*}}{0.134}\, y_{t-5} - \underset{(3.648)^{***}}{7.11\times 10^{-6}}\, FINV_t - \underset{(4.421)^{***}}{8.94\times 10^{-7}}\, SPUSD_t + \underset{(3.686)^{***}}{0.180}\, TR_t$$
$$- \underset{(1.197)}{0.0003}\, CMR_{t-1} - \underset{(2.489)^{**}}{4.94\times 10^{-6}}\, FINV_{t-1} + \underset{(2.430)^{**}}{0.224}\, M1_{t-1} + \underset{(1.272)}{0.204}\, \hat{w}_{t-1} + \underset{(0.340)}{4.128}\, \hat{w}_{t-1}^2$$
$$+ \underset{(0.359)}{166.140}\, \hat{w}_{t-1}^3 - \underset{(0.270)}{5124.961}\, \hat{w}_{t-1}^4 \tag{11}$$

*[The values in parentheses indicate corresponding absolute values of t-ratios; *, **, *** indicate significance at 10%, 5% and 1% levels of significance, respectively.]*

From this regression, it is evident that there is no misspecification in the mean part since all the coefficients associated with $\hat{w}_{t-1}$, $\hat{w}_{t-1}^2$, $\hat{w}_{t-1}^3$ and $\hat{w}_{t-1}^4$ are insignificant. Thus, the performance of the model in (10) is quite satisfactory.

A rise in foreign investment must lead to an appreciation of the domestic currency due to inflow of funds. The direction of the CMR and M1 is in accordance to the standard economic theories. The change in total reserves can also be viewed as a proxy of the intervention activities of the government. As mentioned in the beginning of this paper, the asymmetric nature of the intervention results in large stockpile of reserves. We have obtained a positive relation between the two, i.e., a rise in reserves leading to exchange rate depreciation which is different from the long-run situation in which more reserves indicate better performance of the economy and hence strengthening of the domestic currency. This result could be because of the intervention activities which are undertaken by the RBI to depreciate the Indian rupee. When RBI intervenes, total reserves rises and exchange rate depreciates and hence this could be the justification for this contemporaneous behaviour of change in reserves and exchange rate return. We can argue similarly for the SPUSD (net purchase of foreign exchange) which takes place only when the RBI wants to intervene in the event of some capital inflow. If this purchase is not successful in mopping the excess foreign exchange from the markets then it would essentially lead to an appreciation of the domestic currency.

Finally, although no second order dependence in the residuals has been found, we applied the BDS test due to Brock *et al*. (1996) to detect the existence of any higher order dependence in the residuals. As stated in Section 2, the BDS test is a test where the null hypothesis of independently and identically distributed (*i.i.d.*) errors is tested against the alternative which include serial correlation, higher order dependencies specified by the GARCH model and other unspecified nonlinear forms. Thus, rejection of the null would, in our case where the serial correlation has been duly incorporated in the model, imply that there are other higher order dependences in the residuals of the model. However, a look at the BDS test statistic values in Table 4 makes it quite clear that for all the $(\tilde{\xi}/\sigma, \tilde{m})$ combinations considered, the null cannot be rejected.

Table 4

BDS test statistic values for the residuals of the final model

$\tilde{\xi}/\sigma$	$\tilde{m}$	Value
0.5	2	-0.6604
0.5	3	-2.9380
0.5	4	-1.2664
0.5	5	-0.6220
1	2	-1.0108
1	3	0.1993
1	4	-1.9913
1	5	-1.1209

Note: The values of BDS test statistic, based on residuals of (12), are compared with the simulated values given in Brock et al. (1991). All the test statistic values are insignificant at 5% level of significance. $\tilde{\xi}, \tilde{m}$ *and* σ *stand for distance, embedding dimension and the standard deviation of the linearly filtered data, respectively.*

For instance, the value of the BDS statistic for $\tilde{\xi}/\sigma = 1$ and $\tilde{m} = 2$ has been obtained as -1.0108, and the corresponding critical value (*cf.* Brock et al. (1991)) at 5 per cent level of significance is a number between -2.58 (for T=100) and -2.15 (for T=250). Obviously, the (absolute) computed value is smaller than the (absolute) critical value at 5 per cent level of significance, and hence the null hypothesis of *i.i.d.* errors cannot be rejected for this combination of $\tilde{\xi}/\sigma$ and $\tilde{m}$ values. In fact, there are no cases when the null hypothesis is rejected and we can, therefore, infer that the BDS test suggests that there is no further nonlinear dependence in the residuals. Thus, we can conclude that in terms of standard diagnostic tests on the residuals, the estimated model in (12) is the 'best' linear dynamic single-equation model for determination and predictability of return on India's monthly foreign exchange rate involving relevant macro variables.

5 Conclusions

In this paper, we have first studied the predictability aspect of India's monthly exchange rate return in terms of relevant macroeconomic variables and then obtained the 'best' linear dynamic single-equation model for this time series. Beginning with a set of 24 macro variables which have been found to be relevant in similar studies, mostly on developed economies, and which are also known to have some roles in theoretical studies on exchange rate, we have analyzed the predictive ability –both in-sample and out-of-sample- of each of these macro variables in turn, using specific-to-general as well as general-to-specific model selection criteria. Combining the empirical findings of these two approaches, we have found a set of 10 macro variables which have significant predictive ability for India's exchange rate return. These variables are: reserve money growth, narrow money growth, change in foreign exchange reserve, gross fiscal deficit, sale/purchase of US dollar, change in Federal funds rate, return on US stock index NASDAQ, change in call money rate, rate of change in gold price and change in total foreign investment. Using these macro variables along with the lagged values of these variables as well as of return itself and dummy variables representing month effects, as independent variables, we have estimated a linear dynamic model in single equation framework for India's exchange rate return. In addition to few lag values of return, only five macro variables *viz*., change in foreign exchange reserve, sale / purchase of US dollars, change in call money rate, narrow money growth and change in total foreign investment, were found to be significant.

The model thus obtained was then checked for misspecification in mean and also for presence of any remaining autocorrelation as well as higher order dependences. The final model obtained satisfied all the standard diagnostic tests of model performance. The explanations regarding the roles of all the five macro variables including FINV (with both contemporaneous as well as one-period lag effects) which have been finally found to be significant in exchange rate determination are quite straightforward. A rise in foreign investment evidently leads to an appreciation of domestic currency due to inflow of funds within the economy. The call money market and foreign exchange market are closely linked as there exists arbitrage opportunities between the two markets. When call money rates increase, banks borrow dollars from their overseas branches, swap them for rupees and lend them in call money market. This results in an appreciation of domestic currency. Finally, a growth in money supply usually causes a fall in exchange rate while a rise in domestic stock price results in appreciation of the domestic currency, and this is what has exactly happened in case of India also.

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