Modeling and Forecasting Debt Market Yields: Evidence From India

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Abstract

This paper attempts to evaluate the yield forecasting ability of alternative time series models using monthly data for debt securities in India with residual maturities ranging between 14 days to 25 years. The study period stretches from April 1996 to March 2010. Two univariate models namely Exponential Smoothing Method (ESM) and ARIMA as well as a multivariate VAR model are used for this purpose. The authors find that conventional method like ESM does a better job for both short (three months) as well as long range (twelve months) forecasting of yields compared to more complex and informationally expensive models like ARIMA and multivariate VAR. It is also observed that level of interest rate volatility impacts the yield forecast accuracy for a given period. Short-term yields are more difficult to forecast than yields for securities with longer maturities. Short range forecasting is better than long range forecasting in high interest rate volatility period while there is no such clear pattern, using different time series model, for low interest rate volatility period. The findings have strong implications for both policymakers and debt market players such as bankers, insurance companies and debt funds. The former uses yield forecast information for developing policy formulation while the later employs it for their asset-liability management as well as portfolio management strategies. This research contributes to financial econometrics as well as debt market literature for India which is a fast emerging economy.

Keywords: interest rates, residual maturity, debt market, time series models, commercial banks.
JEL Classification: G12, G17, C22.

Introduction

Debt market is a sub-set of the financial market where participants transact in tradable financial assets for short-term and long-term maturity. World over such market provides optimized liquidity to the financial system, which in turn provides requisite financial resource to the fund deficit entities that require finances for their productive needs.

Depending upon the nature and the need of economic system(s) debt market is controlled/regulated/managed by a designated controller/regulator. Such regulators are statutory institutions in the form of Central Bank. In today's scenario debt markets are wide as well as deep to accommodate the requirements of households, corporate and government, both within and outside the prescribed geographical limits. The economic liberalization together with financial sector reforms has integrated the debt markets globally.

A healthy and matured debt market typifies macro economic scenario and it reflects the appropriate perspectives of fund seekers (issuers of various securities) and provider of funds (subscriber/ investor). The financial association between deficit units and surplus units is based on the premise of 'market-clearing interest rate' that is the rightly discovered price for the resources – a stable (but non static) and predictable interest rate.

For a fast growing economy like India that aspires a minimum GDP growth rate of 10 per cent p.a. over the next decade, debt market has remained a crucial source of funds. India's debt market accounts for approximately 30 per cent of its GDP. Measured by the estimated value of bonds outstanding, it is next only to the Japanese and Korean bond markets in Asia and in terms of volume it is larger than its own equity market. The debt market in India is comprised by government securities (the largest component), bonds issued by public sector undertakings, other government bodies, financial institutions, banks and companies. India has an outstanding issue size of government securities (Central and state) close to US$300 billion and a secondary market turnover of around US$1250 billion (RBI & Clearing Corporation of India Ltd, 2007).

As part of economic reforms the development of government securities (G-Secs) market was initiated in 1992. The G-Secs market up to 1992 was characterized by administered (and often artificially low) rates of interest involving captive investors (essentially banks and insurance companies) due to high Statutory Liquidity Ratio (SLR) requirements[1], absence of a liquid and transparent secondary market for G-Secs and lack of smooth and robust yield curve for pricing of the instruments. Low coupon rates were offered on G-Secs to keep borrowing costs down, which made real rates of return negative for several years in 1980s. During this period volume of debt expanded considerably, particularly short-term debt, due to automatic accommodation to Central government by the Reserve Bank of India

[1] Statutory Liquidity Ratio (SLR) is given under section 24(2A) of the Banking Regulation Act, 1949 as amended by the Banking Laws (Amendment) Act, 1983. According to it a scheduled bank and other banking companies, shall in addition to the Cash Reserve Ratio (CRR) require to maintain under section 18 of the Banking Regulation Act, reserves in (a) cash or (b) gold valued at a price not exceeding the current market price or (c) in unencumbered approved securities or (d) in the form of net balances in current accounts maintained in India by banks with the nationalized banks. The present prescribed percentage of SLR as given by RBI is 24% of the Net Demand and Time Liabilities (NDTL).

(RBI)[1] through the mechanism of ad hoc Treasury Bills[2]. With a captive investor base and interest rate below the market rate, the secondary market for government bonds remained dormant. Artificially low yields on G-Secs affected the yield structure of financial assets in the system, and led to higher lending rates so that banks and other financial institutions can achieve high return on their asset portfolio on overall basis. Important trends and initiatives for Indian debt market are:

1. Prohibition of RBI's subscription to government securities in the primary market w.e.f April 1, 2006, as mandated by the Fiscal Responsibility and Budget Management (FRBM) Act 2003[3].
2. As per Twelfth Finance Commission[4], the role of the Central Government as a financial intermediary for State Goverments is effectively ending, thus leading to State Government's borrowing to be more and more market determined.
3. As Government finances have been improving for both, the Central and State Governments in consonance with the Central and State FRBM Act, the negative savings rate of public sector that had arisen over the last 5 years has turned positive. Therefore, the Gross Domestic Savings will be touching 30 per cent or more of GDP on a sustained basis. Moreover, as the combined fiscal deficit falls, a greater proportion of private financial savings will be available for channelizing into the private sector. This entails higher risks but also opens up the possibility of higher returns. There will then be greater demand for debt securities.
4. An amendment to the Banking Regulation Act 1949 for the removal of 25% minimum SLR.
5. The Government has accepted the recommendation of the Expert Group under Dr. R.H. Patil[5] for energizing the corporate debt market.
6. A significant policy announcement about creation of a single unified exchange-traded market for corporate bonds in India. An internal committee under the chairmanship of SEBI Whole Time Member Dr. T.C. Nair[6] was constituted to chalk out a plan for implementation of a Unified Exchange Traded Corporate Bond Market in India (2006).

Given the size and importance of the debt market for economic development, the asset prices and interest rate information generated in such market is crucial and extremely relevant for different stake holders. For example, households want to know the potential rate of return they expect to earn on their debt investments and corporates want to estimate their future borrowing costs as this will have implications for their capital structure and risk hedging policies. Deposit mobilization and credit creation by banks and other financial institutions is contingent upon the level of interest rates. Even foreign institutional investors' (FIIs) gauge the relative attractiveness of a given debt markets viz a viz other markets by analyzing the interest rate structure. Central banks use interest rate as a monetary tool for controlling inflation and intervening in exchange rate market. Hence modeling and forecasting interest rate is an important economic exercise.

There is a large body of literature that deals with application of time series models to forecast financial variables such as stock market returns and their volatility (Kearns and Pagan, 1991; Rabemananjara and Zakoian, 1993; Nicholls and Tonuri, 1995; Friedmann and Sanddorf-Köhle, 2002), stock index returns (Chen, 1995) and exchange rates (Madura, et al., 1999). Similar time series applications have been used to predict interest rate movement which is critical information for analyzing and trading in money and debt markets.

Several studies have been conducted for both mature as well as emerging markets on interest rate modeling and forecasting. Guidolin and Timmermann (2005) in their study develop a flexible approach to combine forecasts of future spot rates with

[1] Reserve Bank of India (RBI) is the central bank of India established under RBI Act 1934 and started functioning on April 1, 1935 as monetary authority of India. It also functions as a custodian for treasury bills and government securities. It is a member bank of Asian clearing union.

[2] Ad hoc treasury bills (of 91 days maturity which were non marketable) were issued by the government of India to Reserve Bank of India in order to set right the deficit in advance. It was discontinued from April 1997.

[3] The Fiscal Responsibility and Budget Management (FRBM) Act 2003 is meant to provide for the responsibility of the central government to ensure inter-generational equity in fiscal management and long term macro-economic stability by achieving sufficient revenue surplus and removing fiscal impediments in the effective conduct of monetary policy and prudential debt management consistent with fiscal sustainability through limits on the central government borrowings, debt and deficits, greater transparency in fiscal operations of the central government and conducting fiscal policy in a medium term framework and for matters connected therewith or incidental thereto.

[4] 12th Finance commission (2005-10) was appointed on November 1, 2002 under the chairmanship of Dr. C. Rangarajan. One of the recommendations of the commission was that states, like the center, must decide their annual borrowing program, within the framework of their respective fiscal responsibility legislations and that there was also a need to let the states access the market directly for their borrowing requirements (15.7 of Pg 258 of Report of 12th Finance commission).

[5] Dr. R.H. Patil headed a high level experts committee on corporate debt market in India which made recommendations to establish an active corporate debt market. The committee also recommended developing an appropriate market infrastructure and mechanisms for (1) trading platform (2) Clearing and settlement system; (3) risk management; and (4) novation. He recommended that corporate bonds should be treated at par with government securities in all respects like equivalent stamp duties, tax deducted at source, trade reporting, etc. The recommendations were accepted by the finance minister during his budget speech in February 2006.

[6] Dr. T.C. Nair (April 27, 2006) headed a committee which recommended the establishment of a unified exchange traded corporate bond market. This committee was focused on identification of an appropriate mechanism and institutional framework to implement proposals of Patil committee into action.

forecasts from time-series models or macroeconomic variables. Three broad approaches used by them are: random walk, autoregressive models and macroeconomic models. Forward rates appear to be unbiased predictors of movement in future spot rates at longer horizons but perform worse at short horizons. The sample period is January 1950-December 2003, a total of 648 monthly observations. All rates are extracted from the CRSP 6- and 12-month files. The authors proposed a four-state model to capture the dynamics in the US spot and forward rates. They suggested a flexible approach that combines forecasts of future spot rates with other 'testers' that can be viewed as forecasts obtained from alternative model specifications. In an out-of-sample forecasting exercise they found evidence that, particularly at short horizons, combining regime switching forecasts with simpler, univariate time-series forecasts can help reduce the root mean squared forecast error. At longer horizons, they found that imposing theoretical restrictions from the expectations hypothesis linking future spot rates to forward rates helps improve forecasting accuracy. Although the expectations hypothesis is rejected using in-sample tests, it may still be helpful in improving out-of-sample prediction accuracy.

Lima, Luduvice and Tabak (2006) study the relationship between short-term and long-term interest rates and evaluate whether VAR/VEC models are useful in predicting long-term interest rates for Brazil. The data used is daily observations of SELIC[1] and 6-months interest rates from January 1995 to November 2005. Forecasting is done by unrestricted VAR, based on OLS estimates where short- and long-term interest rates are endogenous variables. The empirical results suggest that these models are useful in building qualitative scenarios for the term structure of interest rates, but do not provide good forecasts in terms of accuracy. Furthermore, models that assume that the future path of short-term interest rates (target interest rates) is known by forecasters do not perform better in terms of both directional and forecasting accuracy. Jumah and Kunst (2008) study the forecasting properties of threshold cointegration models for interest rates and inflation, as compared to linear structures. The evaluation of relative forecasting properties is based on standard measures of predictive accuracy such as the mean squared and mean absolute errors by using data from Germany, Japan, the UK, and the USA. The study explores possible threshold cointegration in nominal short- and long-run interest rates with corresponding inflation rates. Traditional cointegration implies perfect mean reversion in real rates and hence confirms the Fisher hypothesis. Threshold cointegration accounts for the possibility that this mean reversion is active only conditional on certain threshold values in the observed variables. They investigate whether findings of such effects can be exploited for prediction. The forecasting experiments demonstrate that, although the threshold cointegration models provide an internally consistent and attractive framework, they are at best weakly supported by empirical evidence.

Similar but very limited efforts have been put to model and forecast interest rates in India.

Dua, Raje and Sahoo (2003) test univariate (ARIMA and ARCH/GARCH) and multivariate models (VAR, VECM and Bayesian VAR) to forecast short- and long-term rates, viz call money rate, 15-91 days treasury-Bill rates and interest rates on government securities with (residual) maturities of one year, five years and ten years. The data is comprised of weekly yields ranging from April 1997 to September 2002. Multivariate models involved factors such as economic liquidity, bank rate, repo rate, yield spread, inflation, credit, foreign interest rates (LIBOR 3 months and 6 months) and forward premium (3 months and 6 months). They find that multivariate models generally outperform univariate models over longer forecast horizons. Overall, the study concludes that forecasting performance of Bayesian VAR models is satisfactory for most interest rates and their superiority is more pronounced for longer forecast horizons.

Bhattacharya, Bhanumurthy and Mallick (2006), in their study, examine the behavior of various Indian interest rates such as call money rates and yields on secondary market securities with maturity periods of 15 to 91 days, 1-year, 5-years and 10-years. They use monthly yields covering the period from April 1996 to March 2005. In the first stage, the study investigates the determinants of interest rates and finds that although the interest rates depend on some domestic marcoeconomic variables such as yield spread and expected exchange rate, they are mainly affected by the movements of international interest rates, although with some lags. The policy variables such as bank rate and federal funds rate did not show any significant impact on any of the interest rates. Bhattacharya et al. (2006) further find that peaks in each interest rate are reached at different time points. Thus, there is a presence of cycles in the domestic interest rates in India, following international rates. Radha and Thenmozhi (2006) develop an appropriate model for forecasting the short-term interest rates, i.e., commercial paper rate, implicit yield on 91 day Treasury bill, overnight MI-

[1] SELIC (Special System for Settlement and Custody) is a system for custody of public bonds issued by the Brazilian Treasury and the central bank. The SELIC interest rate is determined in the secondary market and calculated by the Central Bank of Brazil.

BOR rate and call money rate in India. The data used is daily data of overnight MIBOR and weighted average call money as well as fortnight data of commercial paper rate from January 1999 to June 2004. The study also employes weekly data of implicit yield on 91 day Treasury bill from January 1993 to June 2004. The short-term interest rates are forecasted using univariate models – Random Walk, ARIMA, ARMA-GARCH and ARMA-EGARCH. The appropriate model for forecasting is determined considering goodness of fit. The goodness of fit of the model is tested using correlogram of residuals, LB statistic or Q-test and serial correlation Breusch Godfrey test. The results show that time series of interest rates have volatility clustering effect and hence GARCH based models are more appropriate to forecast than the other models. It is found that for commercial paper rate ARIMA-EGARCH model is most appropriate model, while for implicit yield 91 day Treasury bill, overnight MIBOR rate and call money rate – ARIMA-GARCH model is a better suited model for forecasting. ARIMA and random walk models do not exhibit a good fit.

The Indian work, thus far, mainly confines to G-Secs with residual maturities up to 10 years due to late introduction of such securities with longer maturities, i.e., 11 to 30 years[1]. Previous studies also do not evaluate a wide range of econometric time series models for interest rate forecasting. The present study attempts to fill this important gap in debt market research in India. The study uses yields on a wide range of debt securities from 1996-2010 and has the following objectives: (1) evaluate alternative univariate time series models for forecasting short-term and long-term interest rates; (2) examine how a multivariate VAR model perform viz a viz these univariate models for developing interest rate forecast; (3) test if time series models provide better forecast for short horizon (up to 3 months) compared to long horizon (up to 12 months); and (4) check the relative performance of these models for high and low interest rate volatility periods.

The paper is organized as follows. Section 1 describes data and its sources, while methodological issues are dealt with in section 2. In section 3 we evaluate the relative efficacy of two univariate models – Exponential Smoothing method and ARIMA for forecasting interest rates. Forecasting ability of economic factor based multivariate VAR model is also evaluated in comparison with two univariate models in this section. Summary and concluding remarks are presented in the last section.

1. Data

The data comprises of monthly yields on government securities of varying residual maturities from April 1996 to March 2010. Twenty-nine yield series are employed with residual maturities ranging from 14 days to 25 years. Four of the sample yield series relate to treasury bills and cover the money market segment i.e., 14 days, 15-91 days, 92-182 days, and 183-364 days of residual life. The remaining 25 yield series form part of debt market and relate to government securities with residual life of 1 year to 25 years using integer time periods. The data source is RBI website (www. rbi.org.in). For our analysis, we classify sample yield series into four categories on the basis of residual maturities: short-term (up to 364 days), medium-term (1 to 5 years), long-term (6 to 15 years) and very long-term (16 to 25 years). G-Secs of residual maturities between 26 to 30 years are not included in our analysis owing to lack of adequate data over the study period. Sample yield series beyond residual maturities of 10 years are not available for the total time period resulting in missing observations. These long-term government securities have been introduced in a phased manner over the study period, the details of which are provided in Table 1.

Table 1. Sample securities and their data period

Security (residual life)	Data period
14 days to 10 years	April 1996 to March 2010
11 years to 14 years	April1999 to March 2010
15 years to 19 years	May 1999 to March 2010
20 years	May 2001 to March 2010
21 years to 25 years	October 2001 to March 2010
26 years to 30 years	August 2002 to March 2010

Note: Government securities with maturity above 10 years have been introduced in different years over the study period. This accounts for different data sets (study period) for the sample securities.

We also employ a multivariate model involving key macroeconomic variables for forecasting interest rates, besides the univariate time series models which only use information about yields. Data for these economic variables namely bank rate, bank credit, inflation, liquidity, LIBOR-3m, LIBOR-6m, yield spread, forward premium-3m and forward premium-6m have also been obtained from RBI Website (www.rbi.org.in/home/publication/view) publication. Monthly values of the economic variables are used from April 1996 to March 2010. The variables selection is based on Dua, Raje and Sahoo (2003).

We use standard measure of above mentioned economic variables.

[1] G-Secs of longer maturities (more than 10 years) have been introduced from April 1999 or afterward in India. 26 years to 30 years have been introduced as late as August 2002.

Bank rate is the discount rate or the rate of interest which a central bank charges on the loans and advances extended to commercial banks and other financial institutions. It is one of the monetary tools of the central bank for long-term policy decisions.

Bank credit is the total sum of food and non food credit extended by the scheduled commercial bank. The amount is in rupees crore (one crore is equal to ten million).

Inflation is a rise in the general level of prices of goods and services in an economy over a period of time. Inflation is the annualized percentage change in the general price index over time. Here it is wholesale price index taken from RBI site (as above).

Liquidity is L1 (liquidity aggregate), i.e., total money supply (M3) plus postal deposits given in rupees crore (1 crore = 10 million). It is compiled on a monthly basis. Postal deposits comprise all kinds of post office deposits like saving banks deposits, recurring deposits, time deposits and other deposits.

LIBOR 3m and 6m is the London Interbank offer rate, a floating rate fixed for 3 months and 6 months respectively. It is used for inter bank lending in international market.

Yield spread is the difference between the yield of 10 years residual maturity and 91 days residual maturity. It is calculated from the available sample yield series.

Forward premium 3m and 6m is the Interbank monthly average presented in percent per annum.

2. Methodolgy

The study is conducted in two parts. In part 1 we evaluate relative performance of two univariate time series models in forecasting interest rates. A traditional univariate model namely Exponential Smoothing Method (ESM) is employed. Simple Exponential Smoothing (SES) and Double Exponential Smoothing (DES) are used for stationary and non stationary yield series respectively. In addition, we use a modern univariate model for forecasting interest rates namely Autoregressive Integrated Moving Average (ARIMA) adjusted for any significant ARCH/GARCH effects. In the second part, we examine how a multivariate VAR model performs viz-a-viz the univariate models for forecasting short term and long term interest rates in India.

The estimation process as well as interest rate forecasting is performed twice using two different phases. In phase 1 we employ the period from April 1996 to March 2008 for estimating different models. The estimated models are then used to provide short range, i.e., next three months (April 2008 to June 2008) as well as long range, i.e., next twelve months (April 2008 to March 2009) forecasts for the sample yield series. RMSE and Theil's Inequality Coefficient measures are then computed to evaluate the relative forecasting ability of the two univariate models and the multivariate model.

In phase 2 the model estimation and yield forecasting is then repeated following the above mentioned process after skipping first twelve months of data i.e., April 1996 to March 1997. We thus obtain new short range (April 2009 to June 2009) and long range (April 2009 to March 2010) monthly forecasts for all yield series which are again evaluated using the specified forecast assessment criteria.

We estimate standard deviations using actual yield series for all the sample series for the two non-overlapping forecast periods, i.e., April 2008-2009 and April 2009-2010. Inter period comparison of these standard deviations shall provide an insight about the level of interest rate volatility for the two forecast periods. The exercise shall help us ascertain:

1. Is forecast accuracy contingent upon interest rate volatility?
2. Does the relative performance of alternative forecasting models vary for time periods with different volatility conditions?

We start by testing the stationarity of sample yield series and macroeconomic variables using unit root test. A time series is said to be weakly stationary if it's mean, variance and auto-covariance do not depend on time. Standard inference procedures do not apply to regressions which contain an integrated dependent variable or integrated regressors. Therefore, it is important to check whether a series is stationary or not before using it in a regression. The formal method to test stationarity of a series in the unit root test is Augmented Dickey-Fuller statistic[1] which we evaluate at 5% level of significance.

Next, we estimate the two univariate time series models, i.e., ESM and ARIMA and use them for developing interest rate forecasts. Exponential smoothing is a simple method of adaptive forecasting. Simple Exponential Smoothing (SES) (one parameter) is appropriate for series that move randomly above and below a constant mean with neither trend nor seasonal patterns. Double Exponential Smoothing (DES) (one parameter) method applies the SES twice (using the same parameter) and is appropriate for series with a linear trend. SES is applied to yield series which are stationary at level and DES is applied to yield series which are stationary in the 1st difference form.

[1] Augmented Dickey-Fuller (ADF) test is used to detect if the sample distribution have any unit root. The ADF test is carried out by estimating equation: $yt = \rho yt\text{-}1 + \chi' t\ \delta + \varepsilon t$.

Autoregressive Moving Average (ARMA) model predicts future value of a variable exclusively on its own past values with different lags. Auto Regressive AR (p) is used to predict the future value purely on its own p lags whereas Moving Average MA (q) is forecasting the variable on the past value of its q error terms. The forecasting model ARMA (p, q) is applied on stationary data whereas Autoregressive Integrated Moving Average, ARIMA (p, d, q) model is applied to non stationary data where d is the degree of integration (the level of differencing to make a time series stationary). First, the correlogram is used to display the autocorrelation and partial autocorrelation functions up to the specified order of lags. These functions characterize the pattern of temporal dependence in the series and typically make sense only for time series data.

The selection of best fit models is based on minimization of Schwarz criterion (SIC) and Akaike info criterion (AIC). Volatility of the innovation term (residual) for the mean equation provided by ARIMA is tested for any significant ARCH/GARCH effects, which if present, are used to revise the mean equation before developing interest rate forecasts. The forecast errors are then estimated on month to month basis for each yield series using the two univariate models by taking the difference between forecasted and actual values. RMSE and Theil's inequality coefficients are then estimated using the distribution of forecast errors. The RMSE is a quadratic scoring rule which measures the average magnitude of the error. To estimate RMSE, the difference between forecast and corresponding observed values are squared and then averaged over the sample. Finally, the square root of the average is taken. Since the errors are squared before they are averaged, the RMSE gives a relatively high weight to large errors. This means the RMSE is most useful when large errors are particularly undesirable. The RMSE is the absolute measure of fit and it depends on the scale of the dependent variable. It is used as relative measure to compare forecasts for the same series across different models, the smaller the error, the better is the forecasting ability of that model according to RMSE criterion. The RMSE is given by the following equation:

$$RMSE = [\Sigma(At + n - tFt + n)^2/T]^{0.5},$$

where $At + n$ denotes the actual value of a variable in period ($t + n$), and $tFt + n$ the forecast made in period t for ($t + n$), Theil's inequality coefficient (Theil, 1961), also known as Theil's U, provides a measure of how well a time series of estimated values compares to a corresponding time series of observed values. The statistic measures the degree to which one time series ($\{X_i\}$, i = 1,2,3, ...n) differs from another ($\{Y_i\}$, i = 1, 2, 3, ...n).

Theil's U is calculated as:

$$U = \frac{\sqrt{\frac{1}{n}\sum_i (X_i - Y_i)^2}}{\sqrt{\frac{1}{n}\sum_i X_i^2} + \sqrt{\frac{1}{n}\sum_i Y_i^2}}.$$

Theil's inequality coefficient is useful for comparing different forecast methods. The Theil's inequality coefficient always lies between zero and one, where zero indicates perfect fit. On empirical basis the lower is the value of Theil's statistic for a given time series the better is the quality of forecast. Theil's U is not a scale variant which makes it better tool than RMSE.

For forecasting interest rates on the basis of selected macroeconomic variables multilateral Vector Auto Regression (VAR)[1] method is used. After stationarity test of macroeconomic variables (mentioned in the previous section), Granger linear causality test is performed between sample yield series and macroeconomic variables on paired basis. For example 91 days T-bill and bank rate are one pair similarly 91 days T-bill and inflation is another pair and so on.

In addition, we perform Block Exogeneity Wald test to detect any causality which is missed by Granger Causality test[2]. The VAR type used is Vector Error Correction[3]. It can lead to a better understanding of the nature of any nonstationarity among the different component series and also improve longer-term forecasting over an unconstrained model. Vector Error Correction Estimates which provide value of Standard Errors and t-statistics are calculated using four different lag intervals for endogenous sets. Finally, ordinary least square (OLS) method is used to estimate the VAR equation which develops the relationship between dependent yield series with the relevant macroeconomic variables (that determine yields) and past value of yield series, both up to 4 lags. The forecast errors provided by the multivariate model are

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[1] Vector Auto Regression (VAR) is an econometric model used to measure the interdependencies among multiple time series. It is a natural extension of the univariate autoregressive model to dynamic multivariate time series for forecasting. All the variables in a VAR are treated symmetrically. Forecast from VAR models are quite flexible because they can be made conditional on the potential future paths of specified variables in the model.

[2] The Granger (1969) approach to the question of whether x causes y is to see how much of the current y can be explained by past values of y and then to see whether adding lagged values of x can improve the explanation. y is said to be Granger-caused by x if x helps in the prediction of y, or equivalently if the coefficients on the lagged x's are statistically significant. It uses two-way causation, i.e., x Granger causes y and y Granger causes x. It is important that the statement "x Granger causes y" does not imply that y is the effect or the result of x. Granger causality measures precedence and information content but does not by itself indicate causality in the more common use of the term.

[3] An Error Correction model (ECM) is a dynamical system with the characteristic that the deviation of the current state from its long-run relationship will be fed into its short-run dynamics. ECM is not a model that corrects error in another model. Vector Error Correction Model (VECM) is adding error correction feature to a multi-factor model such as VAR.

then evaluated using RMSE and Theil's inequality coefficient criteria which are already described. The two univariate models and the multivariate VAR model are then compared for their relative forecasting ability. Such a process shall help us in identifying appropriate empirical models for forecasting short and long-term interest rates under different volatility conditions in the Indian environment.

3. Empirical results

We initiate empirical analysis by testing the stationarity of the sample yield series for the two model estimation periods, i.e., April 1996 to March 2008 and April 1997 to March 2009. The results of ADF test and the level of integration of the yield series are given in Table 1. All the sample yield series are integrated to order one and hence are stationary in the rate form for both estimation periods, with exception of yields on short-term securities (14 days, 91 days and 182 days T-bills) which are stationary in the level form (integrated to the order zero) for the first estimation period. Using realized monthly yields, we next estimate the volatility for all yield series for the two adjacent forecast periods, i.e., April 2008 to March 2009 and April 2009 to March 2010. From Table 2 one can observe that yield series exhibit much higher volatility in first forecast period. We, therefore, classify the two forecast periods as high volatility and low volatility periods and shall use this information for further analysis. We also observe that short-term yields (up to 364 days of residual maturities) are more volatile than long-term yields for the high volatility period, while there is no clear pattern of this form in the low volatility period.

3.1. Univariate models. We analyze short range (3 months) forecast results for Exponential Smoothing method (ESM) which are shown in Table 3 (see Appendix). During the high volatility period, RMSE values for short-term securities are lower than those for medium-term securities, but higher than similar values for long- and very long-term securities. In case of low volatility period, RMSE performs best for some medium- and long-term securities (3 to 8 years of maturities). Theil's *U* provides results which are consistent with RMSE for both forecast periods, i.e., 2008-2009 and 2009-2010. Further, short range yield forecast are generally better for all securities in the low volatility period, viz-a-viz high volatility period with a few exceptions.

ESM results for long range forecasting (12 months) are also covered in Table 3. It can be seen using both evaluation criteria that better forecasts are obtained for medium-, long- and very long-term securities compared to short-term securities. Yield forecasts are distinctly superior in the low volatility period for securities of all maturities.

Table 4 (Appendix) provides short range and long range forecast results for ARIMA-ARCH models. It can be observed that no unique ARIMA model emerges as a dominant specification for estimating yield series. ARIMA models provide better short range forecast for long-term securities in the high volatility period and for all securities except short-term securities in the low volatility period. Performing inter-period comparison, short range forecasts are better for short-term securities in high volatility period while they are better for other securities in low volatility period. For long range forecasts ARIMA provides low RMSE values for long-term and very long-term securities in high volatility period and for all securities except those with short-term maturities in the low volatility period. Further, there is a consistency in RMSE and Thiel's *U* results and forecast errors generally tend to be larger in high volatility period compared to low volatility period for all yield series. Better long range forecasts are obtained for all yields for the low volatility period compared to high volatility period.

Comparing the performance of two univariate models for short range yield forecasting, ESM provides lower RMSE and Thiel's *U* values viz a viz ARIMA for both high as well as low volatility periods, with the exception of some very long-term securities (19 to 25 years) for the later period. ESM again provides better long range forecasts than ARIMA for both the volatility periods. Hence, a conventional time series technique like ESM tends to do a better job in providing both short and long range yield forecasts compare to a modern time series technique such as ARIMA in the Indian context.

3.2. Multivariate model. We next examine the efficacy of multivariate VAR model in forecasting yields. We incorporate the macroeconomic factors used by Dua, Raje and Sahoo (2003) for construction of VAR model. A brief description of these economic factors has already been provided in section 1. Granger causality test does not confirm any significant causality between yields (for all maturities) and the economic factors. Given the limitations of Granger causality test discussed in the previous section, we perform an additional causality test, i.e., Block Exogeneity Wald test and find results which are more encouraging. For the first estimation period one (April 1996 to March 2008), inflation and bank rate exhibit relationship with yields for securities up to 4 years of maturity while for securities with 6 to 9 years maturity 3 months Libor emerges as an important economic factor. There seems to be a much stronger relationship between economic factors and long- and very long-term security yields. Seven out of nine factors namely liquidity, bank rate, inflation, libor 3 months and 6 months, forward premium 3 months and 6 months exhibit causality affects with yields for securities ranging between 11 to 25 years of maturity. However, the factor structure is more parsimonious and exhibits no clear pattern across maturities for estimation period two. The relevant economic factors are then used to generate multivariate VAR equations after employing 4 lags for each independent variable. The VAR equations involving security yields as dependent variable are then used to develop yield forecasts after selecting the optimal VAR model based on minimization of Schwartz Criterion (SIC) and Akaike Info Criterion (AIC). These VAR equations for the two estimation periods are shown in Table 5 (in Appendix).

The results for forecast evaluation criteria involving the VAR equations are given in Table 6 (in Appendix). For short range forecast, RMSE and Theil's *U* values are lower for long- and very long-term securities in high volatility period, while they are generally high for short-term securities for low volatility period. Further, short-term securities are better forecasted for high volatility period while other securities are better forecasted for low volatility period. On long range forecast basis, forecast evaluation criteria values are higher for short term securities as compared to other securities. Low volatility period forecasts seem to be better than high volatility period forecasts for all yields. Comparing the forecast ability of two univariate models and multivariate VAR model, one finds that for short range forecast ESM outperforms ARIMA as well as multivariate VAR for both high and low volatility periods. It reports lower RMSE and Theil's *U* values compared to these models. The only exception is the 14 days T-bill yields in the high volatility period where ARIMA does a better job than ESM. For long range forecast, ESM again emerges as a dominant paradigm for developing yield forecast under both the volatility conditions.

Summary and policy observations

In this paper, we attempt to evaluate alternative time series models in terms of their forecasting ability relating to debt market security yields in India. Monthly yield data is used for four types of debt securities: short-term (up to 364 days), medium-term (1-5 years), long-term (6-15 years) and very long-term (16-25 years) from April 1996 to March 2010. There are missing observations for some long-term and very long-term securities predominantly owing to their late introduction in the Indian debt market. We use two univariate time series models, i.e., Exponential Smoothing method (ESM) and ARIMA as well as a multivariate VAR model based on economic factor information. Short range (up to 3 months) and long range (up to 12 months) yield forecasts are developed from these models which are then used to estimate two forecast evaluation criteria, i.e., Root Mean Square Error (RMSE) and Theil's *U*. Lower values for these criteria suggest superior forecasting ability of a given model. The key observations from our analysis are:

1. With very few exceptions, ESM outperforms ARIMA and multivariate VAR models for both short as well as long range yield forecasts relating to debt securities of all maturities.
2. Short-term securities are more difficult to forecast compared to securities with longer maturities.
3. Short range forecasts are distinctly superior to long range forecasts in the period of high interest rate volatility for all debt securities except for short term securities, while there is no such clear pattern based on different time series models, for the low interest rate volatility period. For instance, ESM provides better long range forecast compared to short range forecast, no conclusion could be drawn using ARIMA while multivariate VAR gives better short range forecasts viz-a-viz long range forecasts (with the exception of short-term securities) in the low volatility period.
4. Using alternative models, one cannot conclude that short range forecasts are better for short-term securities for any one of the two interest rate volatility periods.
5. Short range forecasts are better for medium, long- and very long-term securities in low volatility period compared to high volatility period.
6. Long range forecasts are better for all securities in the low interest rate volatility period with the exception of short-term securities.

Our findings have strong implications for policymakers as well as debt market players such as commercial banks, insurance companies and professionally managed debt funds. The former use yield forecast information for developing policy intervention strategy in debt and foreign exchange market. The later use this information for asset-liability management and portfolio management strategies. It is interesting to note that a conventional time series model like Exponential Smoothing Method does a better job than more complex and informationally expansive models such as ARIMA and multivariate VAR and that the level of interest rate volatility impacts yield forecast accuracy. Further the yield forecasts are generally inferior for short-term securities and during the high interest rate volatility period. Our research contributes to both financial econometrics as well as debt market literature especially for an emerging market.

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Appendix

Table 1. Test of stationarity for the sample yield series

The sample yield series are tested for stationarity using ADF test at 5% level of significance. The stationarity results for the two estimation periods are covered in panel A and B respectively.

Panel A: First estimation period (April 1996 to March 2008)			Panel B: Second estimation period (April 1997 to March 2009)		
Residual maturity	ADF t-statistic	Level of integration	Residual maturity	ADF t-statistic	Level of integration
14 days	-3.3099	i=0	14 days	-17.3295	i=1
91 days	-3.3237	i=0	91 days	-16.5887	i=1
182 days	-2.9365	i=0	182 days	-12.9415	i=1
364 days	-12.238	i=1	364 days	-12.4289	i=1
1 year	-8.9385	i=1	1 year	-12.1921	i=1
2 years	-12.6874	i=1	2 years	-11.7176	i=1
3 years	-11.6106	i=1	3 years	-8.5349	i=1
4 years	-11.9093	i=1	4 years	-8.5938	i=1
5 years	-11.3895	i=1	5 years	-8.4772	i=1
6 years	-11.7181	i=1	6 years	-8.1570	i=1
7 years	-12.4697	i=1	7 years	-12.5476	i=1
8 years	-12.3194	i=1	8 years	-12.6605	i=1
9 years	-12.1757	i=1	9 years	-7.9264	i=1
10 years	-12.4211	i=1	10 years	-12.4410	i=1
11 years	-5.5969	i=1	11 years	-6.0597	i=1
12 years	-9.9759	i=1	12 years	-10.8234	i=1
13 years	-10.1646	i=1	13 years	-10.7748	i=1
14 years	-9.7240	i=1	14 years	-10.2788	i=1
15 years	-10.0605	i=1	15 years	-10.4866	i=1
16 years	-9.8101	i=1	16 years	-10.1948	i=1
17 years	-10.0246	i=1	17 years	-10.282	i=1
18 years	-10.0869	i=1	18 years	-10.2305	i=1
19 years	-10.5546	i=1	19 years	-10.0998	i=1
20 years	-8.5715	i=1	20 years	-8.3301	i=1

Table 1 (cont.). Test of stationarity for the sample yield series

Panel A: First estimation period (April 1996 to March 2008)			Panel B: Second estimation period (April 1997 to March 2009)		
Residual maturity	ADF t-statistic	Level of integration	Residual maturity	ADF t-statistic	Level of integration
21 years	-9.2024	i=1	21 years	-8.4652	i=1
22 years	-9.1287	i=1	22 years	-8.4364	i=1
23 years	-8.9767	i=1	23 years	-8.2780	i=1
24 years	-8.8614	i=1	24 years	-8.1845	i=1
25 years	-8.7621	i=1	25 years	-8.1125	i=1

Table 2. Volatility estimates for the sample yield series

We estimate standard deviation (σ) for each sample yield series for the two non-overlapping forecast periods. Panels A and B provide volatility information for first forecast period (2008-2009) and second forecast period (2009-2010) respectively.

Residual maturity	Panel A: Volatility (σ) (2008-2009)	Panel B: Volatility (σ) (2009-2010)
14 days	1.9067	0.3674
91 days	1.7519	0.3022
182 days	1.9476	0.3659
364 days	1.7307	0.4849
1 year	1.8240	0.4502
2 years	1.7385	0.4798
3 years	1.5452	0.4256
4 years	1.4326	0.4343
5 years	1.3703	0.4526
6 years	1.3482	0.4337
7 years	1.2439	0.3227
8 years	1.1984	0.3232
9 years	1.2084	0.3729
10 years	1.2257	0.4793
11 years	1.2015	0.4683
12 years	1.1730	0.4220
13 years	1.0894	0.3860
14 years	1.0528	0.3840
15 years	1.0489	0.3844
16 years	1.0433	0.3642
17 years	1.0388	0.3448
18 years	1.0353	0.3321
19 years	1.0435	0.4064
20 years	1.0466	0.4089
21 years	1.0501	0.4068
22 years	1.0540	0.4062
23 years	1.0581	0.4056
24 years	1.0599	0.4091
25 years	1.0918	0.4110

Table 3. Short and long range forecast results for exponential smoothing method

We provide RMSE and Theil's U values for the sample yield series, both for high volatility (2008-2009) and low volatility (2009-2010) periods. Panel A contains results for short range forecasts (3 months), while panel B contains results for long range forecasts (12 months).

Panel A: Short range forecasts results for 2008-2009 and 2009-2010 for ESM				
Residual maturity	2008-2009		2009-2010	
	RMSE	Theil's in coeff	RMSE	Theil's in coeff
14 days	0.5842	0.0433	0.5417	0.0960
91 days	0.7846	0.0513	0.6035	0.0888
182 days	0.9505	0.0608	0.5973	0.0835
364 days	0.1909	0.0125	0.7080	0.0923
1 year	0.8065	0.0508	0.6053	0.0750
2 years	0.8121	0.0503	0.4680	0.0477
3 years	0.7380	0.0455	0.3429	0.0304
4 years	0.8582	0.0528	0.2751	0.0230

Table 3 (cont.). Short and long range forecast results for exponential smoothing method

Panel A: Short range forecasts results for 2008-2009 and 2009-2010 for ESM				
Residual maturity	2008-2009		2009-2010	
	RMSE	Theil's in coeff	RMSE	Theil's in coeff
5 years	0.6448	0.0397	0.3192	0.0255
6 years	0.5931	0.0365	0.2933	0.0226
7 years	0.5544	0.0341	0.2392	0.0176
8 years	0.5048	0.0310	0.3399	0.0248
9 years	0.4388	0.0270	0.4040	0.0299
10 years	0.3777	0.0233	0.4564	0.0342
11 years	0.3087	0.0187	0.4964	0.0358
12 years	0.3542	0.0213	0.4618	0.0321
13 years	0.4161	0.0248	0.4099	0.0279
14 years	0.4530	0.0269	0.4418	0.0298
15 years	0.5050	0.0300	0.1711	0.0116
16 years	0.5243	0.0311	0.4264	0.0284
17 years	0.5481	0.0324	0.4049	0.0268
18 years	0.5712	0.0337	0.3947	0.0259
19 years	0.5937	0.0350	0.3941	0.0259
20 years	0.5778	0.0339	0.4127	0.0270
21 years	0.5998	0.0353	0.4762	0.0312
22 years	0.5984	0.0352	0.3914	0.0256
23 years	0.5947	0.0349	0.4070	0.0265
24 years	0.5927	0.0348	0.4323	0.0282
25 years	0.5888	0.0345	0.4609	0.0301
Panel B: Long range forecasts results 2008-2009 and 2009-2010 for ESM				
Residual maturity	2008-2009		2009-2010	
	RMSE	Theil's in coeff	RMSE	Theil's in coeff
14 days	1.4228	0.1012	0.6914	0.1169
91 days	1.0088	0.0677	0.5802	0.0865
182 days	1.2197	0.0805	0.4583	0.0593
364 days	1.0798	0.0733	0.4771	0.0554
1 year	1.0683	0.0714	0.5018	0.0540
2 years	0.9610	0.0640	0.3757	0.0330
3 years	0.8844	0.0584	0.2547	0.0200
4 years	0.8888	0.0582	0.2506	0.0187
5 years	0.8752	0.0572	0.2648	0.0190
6 years	0.8888	0.0577	0.2501	0.0176
7 years	0.8996	0.0577	0.2119	0.0147
8 years	0.8862	0.0566	0.2712	0.0186
9 years	0.8787	0.0568	0.3107	0.0214
10 years	0.9101	0.0592	0.2957	0.0201
11 years	0.8831	0.0566	0.3447	0.0228
12 years	0.9103	0.0575	0.3336	0.0216
13 years	0.8722	0.0541	0.2997	0.0191
14 years	0.8064	0.0497	0.3372	0.0215
15 years	0.7926	0.0486	0.2504	0.0160
16 years	0.7685	0.0469	0.2871	0.0180
17 years	0.7542	0.0458	0.2506	0.0156
18 years	0.7408	0.0448	0.2355	0.0146
19 years	0.7650	0.0461	0.3671	0.0226
20 years	0.7510	0.0452	0.3965	0.0244
21 years	0.7976	0.0479	0.3775	0.0232
22 years	0.8085	0.0485	0.3787	0.0233
23 years	0.8176	0.0490	0.3780	0.0232
24 years	0.8201	0.0490	0.3825	0.0235
25 years	0.8346	0.0496	0.3909	0.0240

Table 4. Short and long range forecast results for ARIMA models

For each yield series we estimate ARIMA model separately for two estimation periods, i.e., April 1996 to March 2008 and from April 1997 to March 2009. Model selection has been done on the basis of minimization of Schwartz Criterion (SIC) and Akaike Info Criterion (AIC). The selected models are adjusted for any ARCH/GARCH effects and they are used to develop short range as well as long range forecasts for the sample yield series. Finally, the forecast error information is used to estimate RMSE and Theil's *U*, the two evaluation criteria. Panel A contains results for short range forecasts (3 months), while Panel B contains results for long range forecasts (12 months).

Panel A: Contains results for short range forecasts (3 months) for first estimation period (April 2008-June 2008)						
Residual maturity	Selected model	SIC	AIC	R-squared	RMSE	Theil's in coeff
14 days	ARMA(1,1)	2.7653	2.6475	0.5817	0.3531	0.0268
91 days	ARMA(1,1)	3.5853	3.4679	0.5673	1.0055	0.0668
182 days	ARMA(1,1)	3.4534	3.3356	0.7237	0.9633	0.0618
364 days	AR(1)	1.5422	1.4440	0.9015	0.2221	0.0146
1 year	AR(1)	1.3907	1.2921	0.9186	1.0698	0.0684
2 years	ARMA(3,3)	1.2127	1.0146	0.9605	1.1576	0.0730
3 years	ARMA(3,2)	2.0379	1.8597	0.9673	1.0239	0.0640
4 years	AR(1)	1.0859	0.9878	0.9723	1.0579	0.0664
5 years	ARMA(3,2)	2.1108	1.9326	0.9715	0.9441	0.0590
6 years	ARMA(3,2)	1.1933	1.0150	0.9753	0.9947	0.0625
7 years	ARMA(3,2)	2.4905	2.3122	0.9681	0.9212	0.0577
8 years	ARMA(3,2)	1.1173	0.9391	0.9756	0.9267	0.0582
9 years	AR(1)	0.6903	0.5921	0.9777	0.8765	0.0553
10 years	ARMA(4,3)	2.3246	2.1058	0.9738	0.6758	0.0425
11 years	ARMA(2,1)	0.9840	0.8197	0.9649	0.7782	0.0484
12 years	AR(1)	0.9706	0.8538	0.9630	0.7936	0.0489
13 years	AR(1)	0.7127	0.5960	0.9628	0.7971	0.0487
14 years	ARMA(1,1)	0.8876	0.7474	0.9666	0.8351	0.0508
15 years	AR(1)	0.6784	0.5610	0.9633	0.8975	0.0546
16 years	ARMA(2,1)	0.9277	0.7624	0.9635	0.9295	0.0565
17 years	ARMA(2,1)	0.7197	0.5545	0.9621	0.9390	0.0569
18 years	ARMA(4,3)	0.7789	0.5164	0.9616	0.8981	0.0541
19 years	AR(1)	0.8678	0.7504	0.9599	0.9954	0.0601
20 years	ARMA(2,1)	0.8001	0.6095	0.8839	0.9939	0.0599
21 years	ARMA(2,1)	0.7065	0.5094	0.8684	0.9892	0.0596
22 years	ARMA(2,1)	0.7377	0.5406	0.8625	0.9907	0.0596
23 years	ARMA(2,1)	0.7096	0.5125	0.8621	0.9717	0.0583
24 years	ARMA(2,1)	0.7259	0.5289	0.8624	0.9719	0.0582
25 years	ARMA(2,1)	0.7952	0.5981	0.8642	0.9845	0.0590
Panel A: Contains results for short range forecasts (3 months) for second estimation period (April 2009-June 2009)						
Residual maturity	Selected model	SIC	AIC	R-squared	RMSE	Theil's in coeff
14 days	ARMA(3,3)	2.6697	2.4716	0.7014	1.1265	0.1668
91 days	ARMA(3,3)	2.2689	2.0708	0.8153	1.5893	0.1927
182 days	ARMA(1,1)	3.3466	3.2288	0.7393	2.9537	0.2937
364 days	ARMA(3,3)	2.1260	1.9279	0.8825	1.8892	0.1987
1 year	AR(1)	1.2912	1.1930	0.9269	0.9961	0.1072
2 years	AR(1)	0.9893	0.8912	0.9552	0.5499	0.0519
3 years	ARMA(3,2)	1.0867	0.908449	0.9702	0.4815	0.0408
4 years	ARMA(3,2)	0.9676	0.7893	0.9683	0.4448	0.0357
5 years	AR(1)	0.8014	0.703265	0.9666	1.0337	0.0650
6 years	ARMA(3,2)	1.9296	1.751246	0.9638	0.3475	0.0262
7 years	ARMA(3,2)	0.8096	0.631382	0.9696	0.1479	0.0108
8 years	ARMA(3,2)	1.8964	1.718097	0.9638	0.4132	0.0294
9 years	ARMA(3,2)	1.9752	1.796986	0.9647	0.4311	0.0311
10 years	ARMA(3,2)	2.0373	1.85904	0.9654	0.5269	0.0382
11 years	ARMA(2,1)	0.6702	0.505834	0.9395	0.6036	0.0424
12 years	ARMA(4,3)	0.8989	0.637758	0.9365	0.4062	0.0284
13 years	ARMA(2,1)	0.8660	0.701675	0.9446	0.7643	0.0498
14 years	ARMA(2,1)	0.6498	0.485411	0.9481	0.7298	0.0475

Table 4 (cont.). Short and long range forecast results for ARIMA models

Panel A: Contains results for short range forecasts (3 months) for first estimation period (April 2008-June 2008)						
Residual maturity	Selected model	SIC	AIC	R-squared	RMSE	Theil's in coeff
15 years	ARMA(4,3)	0.9248	0.662257	0.9359	0.2879	0.0193
16 years	ARMA(2,1)	0.9427	0.777392	0.9421	0.2230	0.0148
17 years	ARMA(2,1)	0.6829	0.517645	0.9461	0.4897	0.0315
18 years	ARMA(2,1)	0.6590	0.49378	0.941	0.9546	0.0577
19 years	ARMA(2,1)	0.7743	0.6091	0.9423	0.2886	0.0191
20 years	ARMA(4,3)	0.6823	0.3788	0.8918	0.3167	0.0205
21 years	AR(1)	0.7435	0.6037	0.8577	0.2959	0.0192
22 years	ARMA(3,2)	0.8639	0.6088	0.8645	0.4264	0.0273
23 years	ARMA(1,1)	0.7916	0.6239	0.8571	0.3057	0.0197
24 years	ARMA(3,2)	0.8456	0.5905	0.8667	0.3489	0.0226
25 years	ARMA(3,2)	0.8848	0.6297	0.8640	0.3644	0.0236

Panel B: Contains results for long range forecasts (12 months) for both estimation periods, i.e., April 2008-March 2009 and April 2009-March 2010				
Residual maturity	2008-2009	LR (12 months)	2009-2010	LR (12 months)
	RMS error	Theil's in coeff	RMS error	Theil's in coeff
14 days	1.7566	0.1351	1.0558	0.1427
91 days	1.6759	0.1161	1.4066	0.1673
182 days	1.8967	0.1267	2.9997	0.2766
364 days	1.7190	0.1161	1.2406	0.1264
1 year	1.7040	0.1162	0.6368	0.0644
2 years	1.5730	0.1068	0.4309	0.0381
3 years	1.5260	0.1006	0.3437	0.0273
4 years	1.3419	0.0890	0.3887	0.0294
5 years	1.3944	0.0908	0.5010	0.0388
6 years	1.2617	0.0833	0.3273	0.0232
7 years	1.1837	0.0771	0.3929	0.0278
8 years	1.1472	0.0749	0.2632	0.0181
9 years	1.1217	0.0740	0.3137	0.0218
10 years	1.1876	0.0774	0.3604	0.0247
11 years	1.1163	0.0725	0.5148	0.0346
12 years	1.0965	0.0703	0.7338	0.0494
13 years	1.0337	0.0653	0.8466	0.0515
14 years	1.0152	0.0639	0.7694	0.0469
15 years	1.0373	0.0652	0.5026	0.0326
16 years	1.0437	0.0655	0.4941	0.0318
17 years	1.0437	0.0652	0.4228	0.0258
18 years	0.9711	0.0601	0.4135	0.0262
19 years	1.0705	0.0667	0.9933	0.0647
20 years	1.0721	0.0667	0.4819	0.0303
21 years	1.0749	0.0667	0.3821	0.0239
22 years	1.0804	0.0670	0.3999	0.0248
23 years	1.0762	0.0665	0.3882	0.0242
24 years	1.0792	0.0666	0.5319	0.0334
25 years	1.1294	0.0696	0.5070	0.0318

Table 5. Determinants of debt yields – identifying the factor structure

The economic factors involved in optimal VAR equations (which use debt yields as independent variables) based on minimization of Schwartz Criterion (SIC) and Akaike Info Criterion (AIC) are shown below for the two estimation periods. The VAR equations using specified factor structure are employed to generate short and long range yield forecasts.

	Panel A: First estimation period (April 2008 to March 2009)	Panel B: Second estimation period (April 2009 to March 2010)
	2008-2009	2009-2010
Residual maturity	Selected factors	Selected factors
14 days	Bank rate; inflation	Bank rate; liquidity
91 days	Inflation	Bankrate; fp3m
182 days	Bank rate; inflation; spread	Bank rate; spread

Table 5 (cont.). Determinants of debt yields – identifying the factor structure

	Panel A: First estimation period (April 2008 to March 2009)	Panel B: Second estimation period (April 2009 to March 2010)
	2008-2009	2009-2010
Residual maturity	Selected factors	Selected factors
364 days	Bank rate; infl;spread	Bank rate
1 year	Inflation	Bank rate
2 years	Bank rate; inflation	Bankrate; fp6m
3 years	Bank rate; inflation	Bankrate; fp6m
4 years	Bank rate; inflation	Bank rate
5 years		Bank rate
6 years	L3m	
7 years	L3m	Bank rate; L3M
8 years	L3m	
9 years	L3m	
10 years		
11 years	Liquidity, inflation; FP3M; FP6M	
12 years	Liquidity, inflation; FP3M; FP6M	Bank rate; L3M
13 years	Liquidity, inflation; L3M;	Bank rate; L3M
14 years	Liquidity, inflation	Bank rate; liquidity
15 years	Liquidity, inflation; FP3M; FP6M	Bank rate
16 years	Liquidity, inflation; FP3M; FP6M	Bank rate
17 years	Liquidity, inflation; FP3M; FP6M	Bank rate
18 years	Liquidity, inflation; FP3M; FP6M	Bank rate
19 years	Liquidity, inflation; FP3M; FP6M	L3M; L6M
20 years	Liquidity, bank rate, Inflation; L3M, L6M, FP3M; FP6M	
21 years	Liquidity, inflation; spread, L3M, L6M, FP3M; FP6M	
22 years	Liquidity, inflation; spread, L3M, L6M, FP3M; FP6M	
23 years	Liquidity, inflation; spread, L3M, L6M, FP3M; FP6M	
24 years	Liquidity, inflation; spread, L3M, L6M, FP3M; FP6M	
25 years	Liquidity, inflation; spread, L3M, L6M, FP3M; FP6M	

Table 6. Short and long range forecast results for multivariate VAR model

We generate optimal VAR model for first estimation period (April 1996 to March 2008) and second period (April 1997 to March 2009) using economic factors which were selected based on causality tests. These VAR models were then used to develop yield forecasts. Panels A and B provide RMSE and Theil's *U* value for short and long range forecasts, respectively.

Panel A: Short range forecasts for both estimation periods				
	Forecast for the first period (April 2008 to June 2008)		Forecast for the second period (April 2009 to June 2009)	
	2008-2009	SR	2009-2010	SR (3 months)
Residual maturity	RMS error	Theil's in coeff	RMS error	Theil's in coeff
14 days	0.4100	0.0308	1.2562	0.1822
91 days	0.9481	0.0626	1.5260	0.1864
182 days	1.3642	0.0899	1.2927	0.1538
364 days	0.3843	0.0255	1.7712	0.1888
1 year	1.0962	0.0701	1.0435	0.1118
2 years	1.2490	0.0793	0.5758	0.0543
3 years	1.2193	0.0772	0.4809	0.0408
4 years	1.1908	0.0754	0.4424	0.0356
5 years	1.0440	0.0657	0.3940	0.0306
6 years	1.0425	0.0657	0.2534	0.0193
7 years	0.9927	0.0625	0.2226	0.0164
8 years	0.9459	0.0594	0.2948	0.0212
9 years	0.8912	0.0562	0.3458	0.0253
10 years	0.7007	0.0441	0.4016	0.0296
11 years	0.7448	0.0462	0.4433	0.0315
12 years	0.7759	0.0477	0.3386	0.0235
13 years	0.8821	0.0541	0.3137	0.0213
14 years	0.7746	0.0470	0.5362	0.0354

Table 6 (cont.). Short and long range forecast results for multivariate VAR model

Panel A: Short range forecasts for both estimation periods				
	Forecast for the first period (April 2008 to June 2008)		Forecast for the second period (April 2009 to June 2009)	
	2008-2009	SR	2009-2010	SR (3 months)
Residual maturity	RMS error	Theil's in coeff	RMS error	Theil's in coeff
15 years	0.8851	0.0538	0.4387	0.0290
16 years	0.8941	0.0542	0.3777	0.0249
17 years	0.9301	0.0563	0.3408	0.0222
18 years	0.9769	0.0591	0.3394	0.0220
19 years	0.9689	0.0584	0.2997	0.0196
20 years	0.6563	0.0387	0.2917	0.0190
21 years	0.8180	0.0487	0.2847	0.0185
22 years	0.8841	0.0526	0.2752	0.0179
23 years	0.8840	0.0525	0.2703	0.0176
24 years	0.8893	0.0527	0.2822	0.0184
25 years	0.8707	0.0515	0.3015	0.0197
Panel B: Long range forecasts for both estimation periods				
	Forecast for the first period (April 2008 to June 2008)		Forecast for the second period (April 2009 to June 2009)	
	2008-2009	LR (12months)	2009-2010	LR (12 months)
Residual maturity	RMS error	Theil in coeff	RMS error	Theil in coeff
14 days	1.7314	0.13025	1.1384	0.1522
91 days	1.5975	0.1110	1.3601	0.1625
182 days	1.6964	0.1212	2.1986	0.2193
364 days	1.4834	0.1031	1.2840	0.1287
1 year	1.6631	0.1141	0.6893	0.0692
2 years	1.5335	0.1055	1.5035	0.1029
3 years	1.3628	0.0931	0.4756	0.0382
4 years	1.2741	0.8661	0.5092	0.0389
5 years	1.2671	0.0842	0.5862	0.0434
6 years	1.2433	0.0828	0.6082	0.0442
7 years	1.1754	0.0776	0.8698	0.0632
8 years	1.1482	0.0754	0.4196	0.0294
9 years	1.1226	0.0745	0.5080	0.0359
10 years	1.1349	0.0745	0.6514	0.0458
11 years	1.0712	0.0709	0.5865	0.0398
12 years	1.0850	0.0706	0.9939	0.0679
13 years	1.0787	0.0692	0.9507	0.0638
14 years	1.0108	0.0633	1.0441	0.0649
15 years	1.0733	0.0686	0.4459	0.0286
16 years	1.0688	0.0678	0.4855	0.0311
17 years	1.089992	0.0690	0.5286	0.0337
18 years	1.126751	0.0714	0.5032	0.0320
19 years	1.103105	0.0692	0.9362	0.0605
20 years	0.913463	0.0553	0.6119	0.0388
21 years	0.955614	0.0582	0.5568	0.0352
22 years	1.06232	0.0648	0.5615	0.0355
23 years	1.059317	0.0645	0.5724	0.0361
24 years	1.065036	0.0648	0.5826	0.0368
25 years	1.088641	0.0659	0.5911	0.0374