"Financial liberalization: Efficiency of Indian Money Market".

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Abstract

Our research problem is to study market efficiency of the Indian money market. The concern is that if the money market is efficient then interest rates would stabilize and that there would be a co-movement of different short term rates. For this purpose we have studied four rates, namely, CDs, CPs, T-bills and CMM.

We have used the Juselius-Johansen method of multivariate VAR analysis for studying market integration. Other tools used are- IRF, FEVD and Granger causality.

We arrive at the conclusion that the Indian Money Market is efficient, in the long run. There are contemporaneous effects amongst sub-markets. T-bills help in long run stability and CMM helps in short run adjustment.

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1 Introduction

Money market deals in short term credit instruments whose main purpose is to provide liquidity. The need for liquidity arises due to a gap between current outflows and current inflows of short term liquid funds. The money market instruments have the ability to shift funds quickly from near liquid form to liquid form.

The study of the money market is intended primarily from the point of view of monetary theory and monetary policy. The concern is that if money market was efficient then interest rates would stabilize. There would be uniformity of interest rates across sub markets and any intervention in one part of the market would be efficiently transmitted throughout the money market. If the money market is integrated and hence efficient, there would be minimal disturbances and more so there would not be any systematic differential.

The most important economic function of the money market (Bhole, 2004) is to provide an efficient means for economic agents to adjust their liquidity positions. Almost every economic unit has a recurring problem of liquidity management. The problem occurs because rarely is the timing of cash receipts and cash expenditure perfectly synchronized. Money market allows economic units to bridge the gap between cash receipts and cash expenditure thereby solving their liquidity problems.

The question we need to explore is how efficient money market is? Our research problem is to study market efficiency in money market subsequent to financial liberalization of the early nineties because we expect that after financial liberalization money market would be more integrated and efficient.

What we shall be testing is whether in post financial liberalization the Indian money market has become efficient but the justification for the study also lies in examining the reverse influence. It may be expected that an efficient money market would facilitate the process of financial liberalization.

2 Rationale

The rationale for study of money market arises from three standpoints:

- The new policy framework associated with financial sector reforms. The money market instruments have been liberalized. Many new money market instruments have been introduced. Therefore, we may expect that on one hand money market may become more developed and on the other hand there may be more volatility on account of freeing the controls on money market instruments.
- The process of accelerated economic and business growth along with greater global integration has led to the increased need for liquidity in the money market.
- There is a gap in the literature by which we can identify the need for studying long run efficiency of the Indian money market.

3 Objectives

- To study long run market efficiency or market integration.
- To study the relationship between short run and long run efficiency.
- To study the dynamics of the sub markets of money market.

4 Hypotheses

The crux of the argument in this paper is that financial liberalization has led to the creation of an efficient money market. For this three things are essential:

- Financial liberalization leads to the conditions for an efficient market to be created in the short run[i].
- It is expected that markets would take over in such a manner that they lead to stabilization and market efficiency in the long run.

4.1 Primary Hypotheses

1) One of the primary hypotheses is that with the given conditions of financial liberalization the money market has responded by behaving in an efficient manner in the long run.

To facilitate this primary hypothesis, we have used cointegrating vector, Error Correction mechanism (ECM), speed of adjustment, impulse response function and forecast error variance decomposition (FEVD) for testing a set of secondary hypothesis laid out below.

4.2 Secondary Hypotheses

We now present the secondary hypotheses, which have been tested with the help of appropriate methodologies and statistical tools in our paper.

1a. The interest rates should stabilize in the long run.

1b. The relationship between long run stability and short run stability is efficient.

1c. Shocks to any one of the sub markets would be transmitted to other sub markets and would be absorbed without persistence.

1d. The impact of one sub market on the other differs in degree.

5 Definition and Structure of Money Market

Broadly defined, the money market is the market for financial assets with short maturity. In practice, the cutoff point for 'short' maturity differs between countries, but is usually one year. The short-term financial assets are those, which can be quickly converted into money with minimum transaction cost and minimum loss in the value of assets (Gupta, 2000).

It is about lending liquidity to the financial system. This allows transactions between those entities who need liquidity and those who can provide liquidity. Under conditions of equilibrium in the money market (including its sub markets) the premium paid for obtaining liquidity should be equal to the premium expected for parting with liquidity. This would be determined by market forces in the form of the market rate of interest on short term credit instruments.

In terms of analysis therefore, the rates of interest or the rates on various money market instruments are treated as the prices in the various sub markets of the money market because this would be reflective of the liberalization of the money market. Thus our study concentrates on the study of the rates of interest in the sub markets of the traded money market instruments, namely call money market, commercial paper market, certificates of deposit and treasury bills market.

The Indian money market had been a disintegrated, relatively unorganized, narrow and a shallow market. Till the early nineties, the money market in India had a narrow base, limited number of instruments and participants and controlled interest rates (NCR; 1991, 1998).

Thus, for developing the money market, it was felt necessary by the Reserve Bank of India to have a comprehensive review of the money market. The Reserve Bank of India initiated several measures in post 1987 to widen and deepen the money market (CCR, 1985). Our study however, starts from 1993 since by that year many of the above recommendations were carried out, certain new instruments were introduced and interest rates were liberalized.

6 Financial Liberalization and Efficiency of the Money Market

There is a two way relationship between financial liberalization and efficiency of the money market. Liberalization creates the condition for efficient markets and efficient markets facilitate liberalization. If there are efficient markets, then the process of financial liberalization will be more effective, that is, it is a prerequisite for markets to be efficient. Unless the markets are themselves liberated the markets would not become efficient. In such situations where the markets are not efficient there would be artificial scarcities, persistence of price differentials or interest rates differentials, the possibilities of arbitrage would remain, prices between sub markets would not be linked. There would be short term and long-term volatility and instability of prices and interest rates. In such a situation where market cannot take care of itself it is not possible to talk of financial liberalization before knowing market efficiency. Some amount of intervention and control would be necessary. Hence, before going for policy initiatives for liberalizing the financial sector, we should understand the state of the market so that it can take care of itself. This would happen when market is sufficiently developed. It needs to be seen whether the money market is efficient. There are two dimensions to financial liberalization and market efficiency. On the one hand there is a conceptual framework and on the other hand there are specific measures of financial liberalization in the context of the Indian money market.

7 Review of literature

The extant approaches are based on EMH which is reflected in a random walk model. Random walk model is a non stationary model. Therefore, it does not lend stability to the market. This approach therefore, cannot explain the presence of volatility in different sub markets along with EMH.

Secondly, if prices are volatile in different sub markets, then it means that at given point of time market efficiency does not obtain[ii] because volatility is a clear sign that the demand and supply are not adjusting smoothly. However, the approach that we are adopting is the market integration approach which allows for such price volatility in the short run and yet is able to derive conclusions about long term efficiency. As per market integration approach absolute efficiency is a criterion which may never be attained. It may be an ideal state.

Bhoi and Dhal (1998) have attempted to empirically evaluate the extent of integration of India's financial markets in the post-liberalization period. According to them, there exists a fair degree of convergence of interest rates among the short-term markets-money, credit and gilt markets – but the capital market exhibits fairly isolated behavior.

Joshi (1998) has examined the term structure of interest rates in the Indian economy in order to identify the possible regularities of relationship among various interest rates in government securities market. He has used the well known cointegration and common trends analysis proposed by Gonzalez and Helfand (2001). The interest rates on the following instruments have been considered. They are inter bank call money rate, cut off yield on short term 91-day Treasury bills and on medium term 364-day Treasury bills and redemption yield on long term GOI dated securities. The data used in the study is from January 1993 to February 1998. Their findings are that there is cointegration among interest rates but existence of multiple common trends. Absence of a unique common trend was found by him implying that long run movements of any one interest rate were not dominated by the movements of other interest rates. They further argue that there was presence of cointegration which suggests a long run interlocking of interest rates across markets and a possibility of their future common response to changes in expectations about future monetary policy and economic fundamentals. Their results suggest that the structural policies pursued by the Central bank are of crucial importance in facilitating market integration.

The paper by Parmar (2002) attempts to analyze the behavior of call money market in India. It also attempts to view the interlinkage among three markets that is Call money, Stock market and Foreign exchange market in India during the post-reform period. This paper is being critically examined only from the point of view of the call money market and the methodology used namely; cointegration. The Sample Period is March 1993 till December 2000. The paper tries to see the working of Call Money Market (CMM) or the overnight inter-bank market in India. It also attempts at examining the behavior of CMM and it's inter-linkages with foreign exchange & stock market in post reform India. The inter-linkages, which have been studied under a co-integration framework, suggest the existence of one co-integrating vector among them. Furthermore, this long-term relation implies that the volatility in one of the markets possibly gets transferred to the other markets. So, players in these markets keep shifting their funds in the expectation of earning higher returns and to reduce their exposure to risk. The paper points out towards the methodological need for studying the interrelationship between sub markets. This basis has been incorporated into our methodology.

The paper by Bhatt and Virmani (2005) is about cross border market integration that is between Indian Money Market and USA money market. They have studied instruments upto 3-months maturity. The methodology was to use the interest parity equation. In this paper they have tried to estimate the degree of financial integration between India and the rest of the world, by focusing on the degree of integration of the Indian money market with global markets. The motivation of the paper arises out of capital mobility precipitated by globalization. Here it needs to be pointed out that the money market deals in short term instruments and is essentially about liquidity rather than capital funds. Our approach is to observe the Indian Money Market with respect to domestic market integration especially because short term funds are not likely to be sought from international markets[iii]. There may be an exception to this which is about the foreign exchange market since banks may need liquidity in foreign exchange. However, the foreign exchange market is not similar to the short term credit market, in as much as foreign exchange as an asset is not interest bearing. While in the money market, all other instruments are fixed interest bearing instruments. The paper uses the monthly data on following variables. They are 3-month Treasury Bills auction rate for India- April 1993 to March 2003, 3-month forward Premia-April 1993 to March 2003, 6-month forward Premia-April 1993 to March 2003, Call Money Rate-April 1993 to March 2002 and 3-month

Treasury bill auction rate for U.S. - April 1993 to March 2003. All these variables are taken from RBI Bulletin and Handbook of Statistics, RBI.

The paper shows that the short-term (up to 3 month) money markets in India are getting progressively integrated with those in the USA even though the degree of integration is far from perfect. Covered interest parity was found to hold for while uncovered interest parity fails to hold.

In the paper by Jain and Bhanumurthy (2005), they have examined the issue of integration of financial markets in India. Given the growing movement of capital flows, particularly short-term capital, into the domestic financial markets, it is necessary to examine this issue so as to reap the positive benefits with having stable markets. For this purpose, the study examines this issue in the post-1991 period by using monthly data on call money rates, 91-day Treasury bill rates, Indian Rupee/US dollar exchange rates, and the London Inter Bank Offered Rate (LIBOR). By using a multiple co-integration approach, the study found that there is a strong integration of the domestic call money market with the LIBOR. Though, the study found that there is a long-term co-movement between domestic foreign exchange market and LIBOR, it is not robust. This may be due to frequent intervention by the Central Bank in the foreign exchange market. As the Government securities market in India is still in the developing stage, it was not found to be integrated with the international market. Policy measures (or reforms) are necessary to increase integration of financial markets. This would help in reducing the arbitrage advantage in some specific segment of the financial markets.

In response to Dua (2004) we might observe that in our study there is no degree of freedom problem since there are sufficient numbers of observations and there is no over parameterisation because the number of lags is only four. In respect of the efficacy of multivariate models we would like to observe that period of study in Dua (2004) is from 1997 to 2001 which is not sufficiently large to permit a rigorous analysis of the long-run relationships. By contrast our analysis is based on a 17year period.

A vector autoregressive (VAR) model offers an alternative approach, particularly useful for forecasting purposes. This method is multivariate approach. It must however be pointed out that in Dua (2004) the objective of forecasting was to undertake out of sample forecast for testing the DGP. In our methodology the interest lies in testing for market integration, therefore we have restricted the estimation to within sample forecast except for forecast error variance decomposition (FEVD). The choice of the model does not depend upon any diagnostic for testing for the model specification or efficacy as has been done in the case of Dua (2004) because in our case economic theory or theory of market integration has been used to determine the variables to be included in the model. That is why we have not used other methods like the ARCH/ GARCH models which are essentially univariate methods. Also a natural corollary to the theory of market integration as adopted in our approach is the method of cointegration.

8 Research methodology: Data and model

8.1 Data source and Description

Money market deals with financial claims, assets and securities which have a maturity period of up to one year, for instance, the call money market, treasury bills market, commercial bills market, market in certificates of deposit, commercial paper, collateralized borrowing and lending obligations, repo/ reverse repo and others.

The variables used in the study are the call money rate, commercial paper rate, certificate of deposit rate and 91-day Treasury bills rate. The estimates are based on monthly data from April 1993, through March 2008. The data has been drawn from Report on Currency and Finance, Reserve Bank of India Bulletin, and All India Handbook of Statistics (various issues).

The call rates are the weighted average call money rates on monthly basis. The treasury bills rate is the monthly implicit yield at cut off price in percentage terms.

The data for CPs is given fortnightly. Similarly the data for CDs is also available fortnightly but for some month's transactions are more frequently given and thus we have ignored the values other than those which are closer to 30th of each month. We have not taken the average of lower and the higher end of the rate of interest on monthly basis.

Data for treasury bills is available weekly. In this case also we have taken the values, which are closest to 30th of each month. Here also we have not taken the average of all the transactions given for each month.

The three instruments, that is, the CPs, CDs and the Treasury bills are given in discounted form whereas the CMM instrument is not in discounted form.

Repo/Reverse repo has also not been considered as a money market instrument in our study because of two reasons. First, the repo rate tends to remain the same continuously for many months. It would therefore, behave like a non stochastic variable and cannot be embedded in a cointegrating equation. This implies that the variance would be zero. Second, the repo/reverse repo rate is an administered rate and unlike other money market rates is not market determined. Also, CBLOs has not been considered in the paper since it is a more recent phenomenon.

8.2 Model Specification

We shall be empirically testing for money market efficiency. This has three aspects. Firstly, we shall be establishing the time series properties and we shall test for the precise long term relationship which tells us about long term efficiency. Secondly, we would be testing for the nature of the structure of market integration. Thirdly, we would be testing for the effect of one sub market on the other in a dynamic framework. All these aspects have important policy relevance.

In the first case, apart from testing the ordinary properties of stationarity we need to test for the precise model of stationarity.

When we say that the markets are efficient it means that the fluctuations in rate of interest between the markets, which are integrated, would adjust to each other. This happens through a process of arbitrage, that is, funds flow from the market where the rate of interest is low to the market where the rate of interest is high. So long as market integration is complete, the long run price or the interest rate would stabilize across markets, that is, individually each market is volatile, and jointly the rate of interest across the integrated markets would be stable.

Therefore, our testing framework for market integration has to account for the possibility of non stationarity and volatility in different sub markets and develop a theoretical and empirical framework for establishing market efficiency in the presence of non stationarity and volatility.

With a view to set out testing the market efficiency in the long run, the present study has undertaken the following procedures.

Tests for nonstationarity are first discussed, followed by a description of cointegration, generalized impulse response and decomposition analysis. Finally, we analyze generalized impulse response analysis in a cointegrated VAR model.

8.2.1 Stationary and Non Stationary Time Series

As we begin to develop models for time series, we want to know whether the underlying stochastic process that generated the series can be assumed to be invariant with respect to time. If the characteristics of the stochastic process change over time, that is, the process is non-stationary; it will often be difficult to represent the time series over past and future intervals of time by a simple algebraic model. A vector stochastic process is called weakly stationary if:

All the random vectors have the same mean vector, $E[Y_t]$ = constant for all t.

The variance of all involved random variables are finite, $Var[Y_t]$ = constant and finite.

The covariance matrices of vectors Y_t and Y_{t-h} are time variant and only depend on the distance h, $Cov[Y_t, Y_{t-h}] = f(h)$.

Weak stationarity of a univariate stochastic process requires that the first and second moments of the process exist and are time- invariant. In the presence of non-stationary variables, there might be a spurious regression. A spurious regression has a high R^2 and t-statistics that appear to be significant, but the results are without any economic meaning. Hence one needs to test for the stationarity of the series before formulating a model.

Unit Root Test

Non-stationarity or the presence of a unit root can be tested using the augmented Dickey-Fuller (ADF) test (1979), the Phillips Perron (PP) test (1988) and the KPSS test proposed by Kwiatkowski et al. (1992).

8.2.2 Cointegrating Vector

Cointegration refers to a linear combination of non-stationary variables. Any equilibrium relationship among a set of non-stationary variables implies that their stochastic trends must be linked. After all, the equilibrium relationship means that the variables cannot move independently of each other. This linkage among the stochastic trend necessitates that the variables be cointegrated.

The components of a vector $x_t = (x_{1t}, x_{2t}, \ldots\ldots.. x_{nt})$ are said to be cointegrated of order d, b denoted by $x_t \sim CI(d,b)$ if:

- All components of x_t are integrated of order d
- There exists a vector $\beta = (\beta_1, \ldots\ldots\ldots\ldots.. \beta_n)$ such that the linear combination $\beta x_t = \beta_1 x_{1t} + \ldots\ldots\ldots\ldots\ldots + \beta_n x_{nt}$ is integrated of order (d-b), for d > b.

Vector β is called the Cointegrating Vector.

If x_t has n non-stationary components, there may be at most (n-1) linearly independent cointegrating vectors. The number of cointegrating vectors is called the rank of the cointegrating system. A lack of cointegration among I (d) variables implies no long run equilibrium among the variables.

Cointegrating vector is not unique. If $(\beta_1, \ldots\ldots\ldots\ldots.. \beta_n)$ is a cointegrating vector, then for any non zero value of λ, $(\lambda\beta_1, \ldots\ldots\ldots\ldots.. \lambda\beta_n)$ is also a cointegrating vector.

Typically, one of the variables is used to normalize the cointegrating vector by fixing its coefficient at unity. To normalize the cointegrating vector with respect to $x_{1t,}$ we select $\lambda = 1/\beta_1$.

An important feature of the cointegrated variables is that their time path will be influenced by any deviations from long run equilibrium, that is, $\beta x_t = e_t$, where e_t is the equilibrium error that represents this deviation.

In order to return to its long run equilibrium, at least some variables must respond to the magnitude of disequilibria. This brings us to the Error Correction Model (ECM) in which the short run dynamics of the variables in the system are influenced by deviation from the equilibrium.

Therefore, for any set of cointegrated variable, the relationship can be expressed by an Error Correction (EC) representation & vice versa. This is the Granger Representation Theorem. It says that for any set of I (1) variables, EC & Cointegration are equivalent representations.

8.2.3 Estimating Multivariate Vector Autoregressive Model

VAR is an alternative, non-structural approach to modeling the relationship between several variables. The Vector Autoregressive (VAR) is commonly used for forecasting systems of interrelated time series and for analyzing the dynamic impact of random disturbances on the system of variables. The VAR approach sidesteps the need for structural modeling by modeling every endogenous variable in the system as a function of the lagged values of all of the endogenous variables in the system. The mathematical form of a multivariate VAR is:

$$y_{t} = A_1 y_{t-1} + \ldots\ldots\ldots\ldots + A_p y_{t-p} + e_t \tag{1}$$

where y_t is a k vector of endogenous variables, $A_{1,\ldots\ldots,}$ A_p are matrices of coefficients to be estimated, and e_t is a vector of innovations that may be contemporaneously correlated with each other but are uncorrelated with their own lagged values and uncorrelated with all of the right- hand side variables. In our study k is 4, and it stands for the four sub markets, that is, the CPs rate, CMM rate, CDs rate and the T-bills rate. Since we are estimating multivariate VAR system wherein we believe that these four markets are cointegrated. The whole system of autoregressive equations has to be simultaneously solved as a multivariate VAR system.

$$\begin{bmatrix} P1t \\ P2t \\ P3t \\ P4t \end{bmatrix} = \begin{bmatrix} A11(L)A12(L)A13(L)A14(L) \\ A21(L)A22(L)A23(L)A24(L) \\ A31(L)A32(L)A33(L)A34(L) \\ A41(L)A42(L)A43(L)A44(L) \end{bmatrix} \begin{bmatrix} P1t-1 \\ P2t-1 \\ P3t-1 \\ P4t-1 \end{bmatrix} + \begin{bmatrix} e1t \\ e2t \\ e3t \\ e4t \end{bmatrix} \tag{2}$$

Since only lagged values of the endogenous variables appear on the right- hand side of each equation, there is no issue of simultaneity, and OLS is the appropriate estimation technique. Note the assumption that the disturbances are not serially correlated is not restrictive because adding more lagged y's could absorb any serial correlation.

8.2.4 Estimating Order of the VAR

In an autoregressive process, the present values depend on the past values. But how far do we need to go in the past or how far do we need to take lags because we believe that the data generating process (DGP) specifies that past information influences present values.

If we truncate the lag length then we are arbitrarily deciding the maximum lag length that is likely to influence the present value. If the lag length goes on increasing infinitely and there is no value addition by including further lag values then an optimization method is required by which the lag length is neither arbitrary nor superfluous. Thus the criterion for determining lag length is to choose the maximum lag length that is likely to incorporate the maximum information. Adjusted R explains the relationship between the present and past values. If past values continue to explain the present values as we go on increasing the lag length, the explained variation in present values will increase, leading to increase in adjusted R. In other words the criterion used for the serial correlation test is the standard error of the estimate (converse or the complement of adjusted R). As adjusted R increase the standard error will fall down. Therefore choose the lag length for which standard error is the minimum or adjusted R is the maximum.

OLS can be applied when certain distributional assumptions are met (Classical assumptions). There could be conditions when these assumptions are not met, that is, when the dependant variable does not behave the way we expect it to behave for applying OLS (then use MLE). If the time series available is stationary then apart from the variable not being autoregressive the residual has to be serially uncorrelated.

In addition to the determination of the set of variables to include in the VAR, it is important to determine the appropriate lag length which is the order of the VAR (ρ). Appropriate lag length selection can be critical. If ρ is too small, the model is misspecified; if ρ is too large, degrees of freedom are wasted. For selecting the order of VAR (ρ) for $\rho = 0,1,2\ldots$ p (where ρ represents maximum order) we use Akaike Information Criterion (AIC), Schwartz Bayesian Criterion (SBC) and the likelihood ratio (LR) test.

The AIC and SBC are general tests for model selection. They can be applied across a range of different areas and are like F-test in that they allow for the testing of the relative power of nested models. Each, however, does so by penalizing model, which are over specified (those with 'too many parameters). Thus, by choosing the order of VAR, ρ, high enough the residual serial correlation problem can be avoided, and that for the ρ chosen, the remaining sample for estimation is large enough for the asymptotic theory to work well.

The idea is to calculate these statistics for a range of different values of ρ, and then choose the model in which the statistic is the highest. Note that the SBC statistic imposes a greater 'penalty' for larger number of parameters, this means that the model selected using the SBC statistic will always be at least as parsimonious as the one chosen by AIC.

In practice, the use of SBC is likely to result in selecting a lower order VAR model, as compared to the AIC. But in using both criteria it is important that the maximum order chosen for the VAR is high enough, so that high order VAR specifications are given a reasonable chance of getting selected, if they happen to be appropriate.

Moreover, log likelihood ratio statistics can also be used for order- selection process. These log-likelihood ratio statistics are computed for testing the hypothesis that the order of the VAR is ρ against the alternative that $\rho = 0, 1, 2\ldots$p-1. In testing the hypothesis that the order of the VAR model is p against the alternative that it is p+1, for $\rho = 0, 1, 2, 3\ldots$p-1, can construct the relevant log likelihood statistics for these tests by using the maximized values of the log likelihood function.

After selecting the order of VAR, it is prudent to examine the residuals of individual equations for serial correlation.

8.2.5 Estimation Procedure for Multivariate VAR

For estimating a cointegrating vector, there is a choice between the Engle Granger two step procedure (1987) and Johansen's maximum Likelihood procedure. The second step in estimation involves estimating the rank of the VAR. The order of the VAR would already have been estimated with the help of the test described above. The former uses the method of least squares while the latter is based on MLE. Johansen first developed the procedure and later extended it to a VAR- based cointegration system. It is in this context that the two tests are explained. These are trace tests and maximum eigenvalue test to determine the number of cointegrating relations. Two variables are said to be CI (1, 1) if they are individually I (1), but some linear combination of them is I (0).

Suppose we consider a simple generalization of n variables: -

$$Y_t = A_1 Y_{t-1} + \varepsilon_t \tag{3}$$

So that

$$\begin{aligned} \Delta Y_t &= (A_1 - I)\, Yt_{-1} + \varepsilon_t \\ &= \Pi Y_{t-1} + \varepsilon_t \end{aligned} \tag{4}$$

where Y_t is nx1 vector $(Y_{1t}, Y_{2t} \ldots\ldots\ldots Y_{nt})$

ε_t is nx1 vector $(\varepsilon_{1t}, \varepsilon_{2t} \ldots\ldots\ldots \varepsilon_{nt})$

A_1 is nxn vector of parameters

I is an nxn identity matrix

Π is defined to be $(A_1\text{-}I)$

The rank of $(A_1\text{-}I)$ equals the number of co integrating vectors.

We can generalize the above AR(1) process to include higher order auto regressive process, that is,

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots + A_p Y_{t-p} + \varepsilon_t \tag{5}$$

Such that

$$\Delta y_t = -\Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + A_0 + \varepsilon_t \tag{6}$$

Where

$$\Pi = I_m - \sum_{i=1}^{p} A_i, \qquad (7)$$

$$\Gamma_i = -\sum_{j=i+1}^{p} A_j, \quad i = 1, \ldots, p-1. \qquad (8)$$

If $(A_1 - I)$ consists of all zeros so that rank $(\Pi) = 0$ then $\{X_{it}\}$ sequences are unit root processes, that is, there does not exist any linear combination of $\{X_{it}\}$ that is stationary. So variables are not co integrated.

If rank $(\Pi) = n$ then variables are stationary. In the intermediate case, if rank $(\Pi) = 1$, then there exists a single co integrating vector & Πx_{t-1} gives the EC term. For $1 <$ rank $(\Pi) < n$ there are multiple co integrating vectors.

Granger's representation theorem asserts that if the coefficient matrix Π has reduced rank, $r < k$ then there exist k x r matrices, α and β each with rank r such that $\Pi = \alpha \beta'$ and $\beta' Y_t$ is I (0), then r is the number of cointegrating vector. The elements of α are known as the adjustment parameters in the Vector error correction model (VECM). Johansen's model is to estimate the Π matrix from an unrestricted VAR and to test whether we can reject the restrictions implied by the reduced rank of Π.

The co integrating rank 'r' can also be formally tested by checking the significance of the characteristic roots of Π as rank r equals the number of characteristic roots different from 0. We have following two tests:

Let λi = estimated eigenvalue or the estimated value of the characteristic root

T = number of usable observations

Then,

8.2.6 Trace Test

Ho: number of co integrating vectors $\leq r$

Ha: number of co integrating vectors $> r$

Test statistic:

$$\lambda trace(r) = -T \sum_{i=r+1}^{n} \ln(1-\lambda i) \tag{9}$$

In the trace test the null hypothesis is that the number of cointegrating vectors is less than or equal to r, where r = 1,2… n-1. In each case the null is tested against the relevant alternative.

8.2.7 Maximum Eigenvalue Test

Ho: number of co integrating vectors = r

Ha: number of co integrating vectors = r+1

Test statistic:

$$\lambda max(r, r+1) = -T \ln(1-\lambda_{r+1}) \tag{10}$$

In the max- eigenvalue test, the alternative for r=0 is r=1, then r=1 is tested against t=2 and so on. Since λ_{max} test has a sharper alternative hypothesis as compared to λ_{trace} test, it is used to select the number of cointegrating vectors.

Thus, the trace and maximum eigen value statistics is used to determine the appropriate number of cointegrating relations that are likely to exist among the I (1) variables. The choice of r maximum trace test is more reliable in small sample, thus in case of divergence one should rely on this test.

The stochastic matrix in the VAR model can be written as: Π= α β'. Π contains the parameters of the cointegrating relationship and α is the speed of adjustment parameter. If there is more than one cointegrating relationship, the estimate in β could also contain a combination of cointegrating relationship. Restricted models are obtained by imposing restrictions on β. We can test the restrictions using the Likelihood Ratio tests by using following test statistic:

$$T\sum_{i=1}^{r}[\ln(1-\lambda_{ir})-\ln(1-\lambda_{iu})] \sim \chi^2$$

with degrees of freedom equal to the number of restrictions

Here λ_{ir} = characteristic root of the restricted model

λ_{iu} = characteristic root of the unrestricted model

8.2.8 Model Selection

The cointegrating equation may have intercepts and deterministic trends. The asymptotic distribution of the LR test statistic for the rank test does not have the usual distribution and depends on the assumption made with respect to deterministic trends. The following five possibilities considered by Johansen:

1) No intercept or trend included in the cointegrating equation: This is relevant when there are no intercepts or time trend in the VAR model.
2) Restricted intercept but no trend in the cointegrating vector: In this case an intercept would exist if the restriction is not found to be true.
3) Unrestricted intercept and no trend in the cointegrating vector: With linear deterministic trend in the data, there is also the possibility of intercept but no trend in the cointegrating vector of the VAR model.
4) Unrestricted intercept and restricted trend in the cointegrating equation: In this case a trend would exist if the restriction is not found to be true.
5) Unrestricted intercept and unrestricted trend in the cointegrating vector: With quadratic deterministic trend in data, there is also a possibility of having intercept and trend in the cointegrating vector.

8.2.9 Vector Error Correction and Cointegration Theory

Cointegration is a methodology to study the long term and the dynamic relationship between variables. It is this information content, which is incorporated and reflected in prices and manifests through the cointegrating relationship. The information content is complicated to judge and gather on the basis of a simple regression. It cannot answer the complicated way in which information affects the price whereas the cointegrating framework is capable of capturing and is based on the concept of rational decision-making.

The finding that many macro time series may contain a unit root has spurred the development of the theory of non-stationary time series analysis. Engle and Granger pointed out that a linear combination of two or more non-stationary series may be stationary. If such a stationary, or I (0), linear combination exists, the non stationary (with a unit root), time series is said to be co integrated, The stationary linear combination is called the cointegrating equation and may be interpreted as a long run equilibrium relationship between the variables.

A vector error correction (VEC) model is a restricted multivariate VAR that has cointegrating restrictions built into specification so that it is designed for use with non-stationary series that are known to be co integrated. The VEC specification restricts the long run behavior of the endogenous variables to converge to their cointegrating relationships while allowing a wide range of short run dynamics. The cointegration term is known as the error correction term since the deviation from long run equilibrium is corrected gradually through a series of partial short run adjustments.

Consider the p-dimensional vector autoregressive model with Gaussian errors:

$$y_t = A_1 y_{t-1} + \ldots\ldots + A_p y_{t-p} + A_0 + \varepsilon_t \tag{11}$$

where y_t is an $m \times 1$ vector of I(1) jointly determined variables. The Johansen test assumes that the variables in y_t are I(1). For testing the hypothesis of cointegration the model is reformulated in the vector error-correction form

$$\Delta y_t = -\Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + A_0 + \varepsilon_t \tag{12}$$

where,

$$\Pi = I_m - \sum_{i=1}^{p} A_i, \qquad \Gamma_i = -\sum_{j=i+1}^{p} A_j, \qquad i = 1,.....,p-1.$$

Here the rank of Π is equal to the number of independent cointegrating vectors. If the vector y_t is I(0), Π will be a full rank $m \times m$ matrix. If the elements of vector y_t are I(1) and cointegrated with rank (Π) = r, then $\Pi = \alpha\beta'$, where α and β are $m \times r$ full column rank matrices and there are $r < m$ linear combinations of y_t. The model can easily be extended to include a vector of exogenous I(1) variables.

Under cointegration, the VECM can be represented as

$$\Delta y_t = -\alpha\beta' y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \varepsilon_t \tag{13}$$

where α is the matrix of adjustment coefficients. If there are non-zero cointegrating vectors, then some of the elements of α must also be non zero to keep the elements of y_t from diverging from equilibrium[iv].

It follows from the theorem that in the presence of such divergence between short run and long run, as the series are I (1)s, the estimation of the multivariate VAR in level would be enough. Then VAR can be constructed in first differences with the addition of an error correction term to capture the difference between the short run dynamics and the long-term relationship. In the absence of cointegration, we get VAR in first difference without any error correction term because Δy_t does not respond to previous period's deviation from long run equilibrium.

8.2.10 Diagnostics Tests

Given the crucial role of the diagnostics tests in the analysis of the results, it is important to carry out the tests to confirm the assumption of normality. A popular test for this purpose is the Jarque Bera test (1980).

Another diagnostic test is the Serial Correlation LM Test. This test is an alternative to the Q-statistics for testing serial correlation. The test belongs to the class of asymptotic (large sample) tests known as Lagrange multiplier (LM) tests.

The third test is the CUSUM Test (Brown, Durbin, and Evans, 1975) which is based on the cumulative sum of the recursive residuals. This option plots the cumulative sum together with the 5percent critical lines. The test finds parameter instability if the cumulative sum goes outside the area between the two critical lines.

8.2.11 Testing for Money Market Efficiency

Granger Causality Test

One important issue in the analysis of the money market integration is the extent to which changes in returns in one market are transmitted from one market to another. This issue can be examined by Granger non causality tests applied to our model. If the presence of cointegration is established, the concept of Granger causality can also be tested in the VECM framework. For example, if two variables are cointegrated, that is, they have a common stochastic trend, and then causality in the Granger (temporal) sense must exist in at least one direction (Granger, 1986). Thus in a two variable vector error correction model, we say that the first variable does not Granger cause the second if the lags of the first variable and the error correction term are jointly not significantly different from zero. This is tested by a joint F or Wald χ^2 test.

Granger (1969) introduced a concept of causality that is based on the idea that a cause cannot come after the effect. Thus if a variable X affects a variable Y, the former should help to predict the latter. X_t fails to granger cause Y_t if for all s > 0, the mean squared error (MSE) forecast of Y_{t+s} based on (Y_t, Y_{t-1}…) is the same as MSE of the forecast of Y_{t+s} based on (X_t, X_{t-1}…) & (Y_t, Y_{t-1}…). Consider the two variable VAR model with p lags.

$$Y_{t} = \Sigma A_k Y_{t-k} + \Sigma \beta_k X_{t-k} + \alpha + \mu_t \tag{14}$$

We say that a time series Y_t is Granger caused by a time series X_t if lagged Y_t and X_t explain contemporaneous Y_t. More specifically if the null hypothesis $\beta_k = 0$ (for all k) is rejected, then Y_t is Granger caused by X. Conversely if we cannot reject the null hypothesis, then Y_t is not Granger caused by X_t. The null hypothesis is tested by the F- value

$$F(p, n\text{-}2p\text{-}1) = \{(RSSR\text{-}USSR)/ p\}/ (USSR/ n\text{-}2p\text{-}1) \tag{15}$$

where n is the number of observations, p is the number of restrictions. USSR is the sum of squared residuals of the unrestricted model and RSSR represents the sum of squared residuals restricted by $\beta_k = 0$ (for all k) of the same estimation. This F- test is called Granger causality test.

With VEC terms, it becomes necessary to reinterpret the Granger causality in a cointegrated system. In a cointegrated system, a Y_t variable is not Granger caused by Xt, if and only if lagged values of ΔX_t does not enter the ΔY_t equation and if Y_t does not respond to the deviation from the long run equilibrium. Thus the null hypothesis is $A_k = 0$ for all k= 1, 2,…, p and the error correction term equals zero. This is the standard F-test as described above. If Granger causality displays a result which implies that all sub markets mutually cause each other then it is indicative of system of a long run relationship amongst sub markets whereby, all markets are mutually dependent on each other. Under such circumstances, methodologically it is indicative of the need for implementing a multivariate VAR where all variables are interdependent. In further analysis we estimate a multivariate VAR as against any other candidate like an Autoregressive Distributed lag model (ARDL) model which treats one of the variables as being dependent.

8.2.12 Impulse Response Analysis

Dynamic relationships among variables in VAR models can be analyzed using innovation accounting methods that include impulse response functions and variance decompositions.

An impulse response function measures the time profile of the effect of shocks at a given point in time on the future values of variables of a dynamical system.

An impulse response function is created by converting the VAR model (p) to the vector moving average model of infinite order VMA (∞). It traces the effects of one standard deviation shock to one of the impulses μ_t on current and future values of the endogenous variables Y_t in the converted form of a stable VAR (p) process with a MA (∞) representation. The moving average representation is an especially useful tool to examine the interaction between variables in the VAR.

The impulses are usually correlated, so that they have a common component that cannot be associated with a specific variable. A common method of dealing with this issue is to attribute all of the effects of any component to one variable that comes first in the VMA (∞) model. More technically, the error terms are orthogonalised by cholesky decomposition, so that the covariance matrix of the resulting impulses is diagonal while this method is widely used, it is rather arbitrary and changing the cholesky ordering of the variables could dramatically change the impulse response.

A major limitation of the conventional method advocated by Sims (1980, 81) is that the impulse response analysis is sensitive to the ordering of variables in the VAR (see Lutkepohl, 1991). In this approach, the underlying shocks to the VAR model are orthogonalised using the Cholesky decomposition of the variance-covariance matrix of the errors, $\Sigma = E(\varepsilon_t \varepsilon_t') = PP'$, where P is a lower triangular matrix. Thus a new sequence of errors is created with the errors being orthogonal to each other, and contemporaneously uncorrelated with unit standard errors. Therefore the effect of a shock to any one of these orthogonalised errors is unambiguous because it is not correlated with the other orthogonalised errors.

Generalized impulse responses overcome the problem of dependence of the orthogonalised impulse responses on the ordering of the variables in the VAR. Koop et. al (1996) originally proposed the generalized impulse response functions (GIRF) for non-linear dynamical systems but this was further developed by Pesaran and Shin (1998) for linear multivariate models. An added advantage of the GIRF is that since no orthogonalised assumption is imposed, it is possible to examine the initial impact of responses of each variable to shocks to any of the other variables.

The generalized impulse response analysis can be described in the following way[v]. Consider a VAR (p) model:

$$x_t = \sum_{i=1}^{p} \Phi_i x_{t-i} + \varepsilon_t, \qquad t = 1,2,\ldots, T. \tag{16}$$

where $x_t = (x_{1t}, x_{2t}, \ldots, x_{mt})'$ is an $m \times 1$ vector of jointly determined dependent variables and $\{\Phi_i, i=1,2,\ldots,p\}$ are $m \times m$ coefficient matrices.

If x_t is covariance-stationary, the above model can be written as an infinite MA representation:

$$x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}, \qquad t = 1,2,,\ldots,T. \tag{17}$$

where $m \times m$ coefficient matrices A_i can be obtained using the following recursive relations:

$$A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \ldots + \Phi_p A_{i-p}, \quad i = 1, 2\ldots \tag{18}$$

with $A_0 = I_m$ and $A_i = O$ for $i < 0$.

Consider the effect of a hypothetical $m \times 1$ vector of shocks of size $\delta = (\delta_1, \ldots, \delta_m)'$ hitting the economy at time t compared with a base-line profile at time t+n, given the economy's history.

The generalized impulse response function of x_t at horizon n, is given by:

$$GI_x(n, \delta, \Omega_{t-1}) = E(x_{t+n} \mid \varepsilon_t = \delta, \Omega_{t-1}) - E(x_{t+n} \mid \Omega_{t-1}) \tag{19}$$

where the history of the process up to period t-1 is known and denoted by the non-decreasing information set Ω_t.

Here the appropriate choice of hypothesized vector of shocks, δ, is central to the properties of the impulse response function. By using Sims' (1980) Cholesky decomposition of Σ $(=E(\varepsilon_t \varepsilon_t')) = PP'$, the $m \times 1$ vector of the orthogonalised impulse response function of a unit shock to the jth equation on x_{t+n} is given by:

$$\psi_j^o = A_n P e_j, \qquad n = 0, 1, 2, \tag{20}$$

where e_j is an $m \times 1$ vector with unity as its jth element and zero elsewhere.

However, Pesaran and Shin (1998) suggest shocking only one element (say j^{th} element), instead of shocking all elements of ε_t, and integrate out the effects of other shocks using an assumed or historically observed distribution of errors. Thus, now the generalized impulse response equation can be written as

$$GI_x(n, \delta_j, \Omega_{t-1}) = E(x_{t+n} | \varepsilon_{jt} = \delta_j, \Omega_{t-1}) - E(x_{t+n} | \Omega_{t-1}) \tag{21}$$

If the errors are correlated a shock to one error will be associated with changes in the other errors. Assuming that ε_t has a multivariate normal distribution, i.e., $\varepsilon_t \sim N(0, \Sigma)$, we have

$$E(\varepsilon_t | \varepsilon_{jt} = \delta_j) = (\sigma_{1j}, \sigma_{2j}, \cdots, \sigma_{mj})' \sigma_{jj}^{-1} \delta_j = \Sigma e_j \sigma_{jj}^{-1} \delta_j \tag{22}$$

This gives the predicted shock in each error given a shock to ε_{jt}, based on the typical correlation observed historically between the errors. This is different from the case where the disturbances are orthogonal and the shock only changes the jth error as follows:

$$E(\varepsilon_t | \varepsilon_{jt} = \delta_j) = \delta_j e_j \tag{23}$$

By setting $\delta_j = \sqrt{\sigma_{jj}}$ in equation (6.38), that is, measuring the shock by one standard deviation, the generalized impulse response function that measures the effect of a one standard error shock to the jth equation at time t on expected values of x at time t + n is given by

$$\psi_j^g(n) = \sigma_{jj}^{-\frac{1}{2}} A_n \Sigma e_j, \quad n = 0, 1, 2, \ldots \tag{24}$$

These impulse responses can be uniquely estimated and take full account of the historical patterns of correlations observed amongst the different shocks. Unlike the orthogonalised impulse responses, these are invariant to the ordering of the variables in the VAR.

8.2.14 Variance Decomposition Analysis

Variance decomposition provides a different method of depicting the system dynamics. Impulse response functions trace the effects of a shock to an endogenous variable on the variables in the VAR. By contrast, variance decomposition decomposes variation in an endogenous variable in the VAR. The variance decomposition gives information about the relative importance of each random innovation to the variables in the VAR. Variance decomposes variation in a targeted endogenous variable Y_t into the component shocks to all the endogenous variables in the VMA (∞) model, and provides information about the relative importance of each random impulse μ_t to the targeted variable. The variance decomposition gives information about the relative importance of each random innovation to the variables in the VAR.

Impulse response analysis and variance decomposition, together called innovation accounting can be useful tools to examine the dynamic relationships among economic variables.

The forecast error variance decompositions provide a breakdown of the variance of the n-step ahead forecast errors of variable i which is accounted for by the innovations in variable j in the VAR. As in the case of the orthogonalised impulse response functions, the orthogonalised forecast error variance decompositions are also not invariant to the ordering of the variables in the VAR. Thus, we use the generalized variance decomposition which considers the proportion of the N-step ahead forecast errors of x_t which is explained by conditioning on the non-orthogonalised shocks, $\varepsilon_{it}, \varepsilon_{it+1}, \ldots, \varepsilon_{it+N}$, but explicitly allows for the contemporaneous correlation between these shocks and the shocks to the other equations in the system.

Thus, while the orthogonalised variance decomposition (Lutkepohl, 1991) is given by,

$$\theta_{ij}^{0}(n) = \frac{\sum_{l=0}^{n} (e_i' A_l P e_j)^2}{\sum_{l=0}^{n} (e_i' A_l \Sigma A_l' e_i)} \qquad i,j = 1, 2, \ldots, m. \tag{25}$$

the generalized variance decomposition is given by,

$$\theta_{ij}^{g}(n) = \frac{\sigma_{ii}^{-1} \sum_{l=0}^{n} (e_i' A_l \Sigma e_j)^2}{\sum_{l=0}^{n} (e_i' A_l \Sigma A_l' e_i)} \qquad i,j = 1, 2, \ldots, m \tag{26}$$

While by construction $\sum_{j=1}^{m} \theta_{ij}^{0}(n) = 1$, due to the non-zero covariance between the non-orthogonalised shocks, $\sum_{j=1}^{m} \theta_{ij}^{g}(n) \neq 1$.

Pesaran and Shin (1998) have shown that the orthogonalised and the generalized impulse responses as well as forecast error variance decompositions coincide if Σ is diagonal and for a non-diagonal error variance matrix they coincide only in the case of shocks to the first equation in the VAR. Thus to select between the orthogonalised and generalized analysis, we first test if Σ is diagonal or not. The null hypothesis is:

H_0: $\sigma_{ij} = 0$, for all $\forall\ i \neq j$.

where σ_{ij} stands for the contemporaneous covariance between the shocks in the endogenous variables.

The Likelihood-ratio test statistic is given by

$$LR\ (H_0|H_1) = 2\ (LL_U - LL_R) \tag{27}$$

where LL_U and LL_R are the maximized values of the log-likelihood function under H_1 (the unrestricted model) and under H_0 (the restricted model), respectively. LL_U is the system log-likelihood and LL_R is computed as the sum of the log-likelihood values from the individual equations. The LR test statistic follows a χ^2 distribution with degrees of freedom equal to the number of endogenous variables.

8.2.15 Generalized Impulse Response Analysis in a Cointegrated VAR Model

Some of the instruments and rates are often administered and therefore, do not have the necessary property to allow efficient price adjustment across markets. They cannot form the basis of long term efficiency since they do not have the necessary flexibility. At best they could be used as policy interventions but would be effective only if markets are free enough and possess the long term structure for ensuring market integration and efficiency otherwise such interventions are only likely to lead to shocks which do not resolve them adequately, quickly and decisively through the operation of market forces.

The long run efficiency can also be gauged from the impulse response across markets. This is necessary because the manner in which efficiency has been defined it implies that there are effects which are transmitted from one market to the other but because markets are efficient they are able to adequately, quickly and decisively resolve these effects. Further in our conception of the structure of market integration we are hypothesizing that markets are integrated as a network. It is therefore, necessary to not only test for long run market integration but to test how markets behave in the event of shocks being transmitted to them. In the context of networked markets the shocks could therefore arise from any market and affect any other market. Therefore, a shock is not just a unilateral shock but could appear as multilateral shock.

The generalized impulse response analysis can be extended to a cointegrated VAR model. Consider the following Vector Error Correction Model (VECM) described by Pesaran and Shin (1998):

$$\Delta x_t = -\Pi x_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta x_{t-i} + \varepsilon_t, \quad t = 1,2,\ldots,T. \qquad (28)$$

where $\Pi = I_m - \sum_{i=1}^{p} \Phi_i, \; \Gamma_i = -\sum_{j=i+1}^{p} \Phi_j$ for i = 1,2,…,p-1, and Λ is an $m \times g$ matrix of unknown coefficients.

If x_t is first-difference stationary, Δx_t can be written as the infinite moving average representation,

$$\Delta x_t = \sum_{i=0}^{\infty} C_i \varepsilon_{t-i}, \quad t = 1, 2, \ldots, T. \qquad (29)$$

The generalized impulse response function of x_{t+n} with respect to a shock in the jth equation is given by:

$$\psi^g_{x,j}(n) = \sigma_{jj}^{-\frac{1}{2}} B_n \Sigma e_j, \quad n = 0, 1, 2, \ldots \qquad (30)$$

where $B_n = \sum_{j=0}^{n} C_j$ is the cumulative effect matrix with $B_0 = C_0 = I_m$.

Similarly, the orthogonalised impulse response function of x_t with respect to a variable-specific shock in the jth equation are given by

$$\psi^{o}_{x,j}(n) = B_n P e_j, \quad n = 0,1,2,\ldots \tag{31}$$

Once again the two-impulse response functions as well as the forecast error variance decompositions coincide if either the error variance-covariance matrix is diagonal or for a non-diagonal error variance-covariance matrix, if a shock is induced in the first equation in the VAR.

9 Empirical Investigation

9.1 Unit Root Testing

We have done three tests to find out if the unit roots exist or not. Using the majority rule we conclude that all the variables have a unit root. Thus, we can say from these tests that the series CMM, CPs, CDs and T-bills are non-stationary.

Next, we need to determine if these series are integrated of the same order. We again carry out the ADF test at first difference of each of these series. We find that the first difference of the series CMM, CPs, CDs and T-bills are stationary. Testing for stationarity of differences of each variable confirms that all the variables are integrated of order one.

9.2 Testing for Order of the VAR

The second econometric step is to determine the lag length of the VAR model. We use AIC, SBC and LR to aid us in choosing the lag length to ensure robustness of our results. In Table I, the lag length selection criterion is tabulated. The columns of the table give the test statistic for lag length selection- LR, AIC and SBC, while the rows give the value of the test statistic at various lag lengths ranging from 1 to 8.

In this Table, with choosing P=8, we test the hypothesis that the lag length is p=1, 2…8. The AIC and the SBC select the orders 4 and 1 respectively. The adjusted LR test statistics reject order 1, 2, and 3 but does not reject a VAR of order 4. In the light of the above we choose the VAR (4) model. It is quite usual for the SBC to select a lower order VAR as compared with the AIC. We have used the majority rule. As per the theory, we have to select the maximum lag length because it includes the maximum information **(See Table I)**.

Table I Here

9.3 Testing for Cointegration

To test for cointegration, we use the trace test and maximum eigenvalue test **(See Table II)**.

Table II Here

The first column indicates the null hypothesis; this is tested against the alternative hypothesis given in second column. The third column gives the test statistic while the fourth and fifth column report out the critical value of the test statistic at 5 percent and 10 percent level of significance.

The chosen model is the "No intercept and no trend in the cointegrating vector". In model 2, when a restriction is imposed about existence of an intercept, we test to see whether the intercept is zero or not. Since in our case the restriction is found to be true that the intercept is zero we do not choose model 2. Similarly in model 4, when a restriction is imposed about existence of slope, we test to see whether the slope is zero or not. Since in our case the results are found to be 'non convergent' we do not choose model 4. Since the test for existence of an intercept and slope indicate that the intercept and slope do not exist, we therefore, select model 1 without intercept and slope against unrestricted intercept and unrestricted slope in model 3 and 5 respectively.

Thus the selected model is model 1 which implies that there is no intercept and trend. In the multivariate VAR, the interest rates between different sub markets differ. We may expect an intercept because there would be some minimum rate of interest. However, in the long run sense in a VAR a single intercept may not represent the minimum interest rate in the money market as a whole since there are four different rates. Secondly, the implication of having a trend is that the interest rates in the long run are bound to increase monotonically so that unusually high interest rates may be achieved. This seems to be counter intuitive in real terms.

In the trace test, we first consider the hypothesis that the variables are not cointegrated against the alternative of one or more cointegrating vectors. Since the calculated value exceeds the 10 percent and 5 percent critical value of the λ_{trac} statistic, it is possible to reject the null hypothesis of no cointegrating vectors and accept the alternative of one or more cointegrating vectors. Next we use λ_{trace} (1) statistic to test the null of $r \leq 1$ against the alternative of two or more cointegrating vectors. We again reject the null hypothesis at both 5 and 10 percent significance level. Next we use λ_{trace} (2) statistic to test the null of $r \leq 2$ against the alternative of three or more cointegrating vectors. We cannot reject the null hypothesis at both 5 and 10 percent significance level. Thus trace test indicates two cointegrating vectors at 5 percent and 10 percent level of significance.

The results are reinforced by the max- eigenvalue test. The null hypothesis of no cointegrating vectors (r=0) against the alternative of r =1 is rejected at 10 percent and 5 percent level. Next we test the null of $r \leq 1$ against the alternative of r =2. We again reject the null hypothesis both at 5 and 10 percent level of significance. Next we test the null of $r \leq 2$ against the alternative of r =3. We cannot reject the null hypothesis both at 5 percent and 10 percent level of significance. Thus there exist two cointegrating relations in the model. The rank of the VAR is two

In the estimation of the cointegrating vector, it is possible to specify different models by normalizing on each of the markets separately. In our case we have normalized on CPs. Therefore, it would be noticed that the coefficient for CPs are normalized at (-) 1. Although there exist two cointegrating vectors, we find that the variables in the second cointegrating vector do not have expected signs, as suggested by the theoretical model. The second cointegrating vector suggests that while CPs is positively related to CMM and CDs, it is negatively related to T-bills rate. The signs are therefore not economically plausible **(See Table III)**.

Table III Here

Therefore, we drop the second cointegrating vector and choose only the first cointegrating vector. After dropping the second cointegrating vector we get the following cointegrating vector after normalizing it with respect to CPs. When we normalized on the other variables and estimated the VAR, the signs of the coefficients were not consistent. It would be pertinent to recapitulate that we have selected a particular model of unit roots, an order of lag length four, selected one cointegrating vector and normalized on CPs. `

$\beta = (\beta_1, \beta_2, \beta_3, \beta_4)$

$\beta_{1\,=}$ 1 (coefficient of CPs)

$\beta_2 = 0.024$ (coefficient of CMM)

$\beta_3 = 0.489$ (coefficient of CDs)

$\beta_4 = 0.700$ (coefficient of T-bills)

The co-integrating equation is:

$$\underset{}{\text{CPs}} = \underset{(.799)}{0.024\text{CMM}} + \underset{(.001)}{0.489\text{CDs}} + \underset{(.003)}{0.700\text{T-bills}} \qquad (32)$$

In the above cointegrating vector, certificates of deposits and treasury bills rate are significant at 5 percent level of significance. CMM is not significant which shows that although long run efficiency exists in an overall sense, CMM is the weakest market in terms of long run efficiency **(See Table IV)**.

Table IV Here

The above cointegrating vector tells us about the impulse response relationship. Since the nature of the relationship is positive it shows that the long term relationship has the desirable effect of co movement in rate of interest. The second aspect is to study the magnitude of the relationship amongst different markets which refers to the coefficients of the money market rates being normalized on CPs. As expected, T-bills play the major role in stabilizing the market in the long run since its impact is the greatest. Next in that order, CDs play a vital role while call money market which is a relatively volatile market plays a minor role in long term market interest rates. Even this minor impact is not very consistent because the p-value is not consistent. This is corroborated by the significance level in which case it is apparent that call money market alone is a market which is not highly significant. On the whole the equation tells us that the Indian Money Market is efficient in the long run in an overall sense although the role and significance of different markets vary amongst each other.

After having discussed the results of our cointegration analysis we would like to compare results from Jena et al (2002), since this is the paper which is comparable to our study here. They have found that while 91 day T-bills are cointegrated with call money rate, they are not cointegrated with CPs and CDs rates. There are two pertinent results from their study which are at variance with our study.

> "The slope coefficients between TB-91 and CMR show that there is strong long run relationship between Call money market and Treasury bill market. ….Within the money market, all the three variables namely, CMR, CPR, and CDR are cointegrated."

While their study has found the above, our findings are that T-bills play a major role in stabilizing the market in the long run since its impact is the greatest. Next in that order, CDs play a vital role while call money market which is a relatively volatile market plays a minor role in long term market interest rates. This is corroborated by the significance level in which case it is apparent that call money market alone is a market whose coefficient is not highly significant.

While they have commented on the various coefficients amongst the sub markets they are not comparable with ours because the period is different.

In comparison to Jena et al (2002), our analysis is much more elaborate since it takes care of many other aspects of market efficiency such as short term adjustment which is measured through ECM, resolution of shocks which is measured through Impulse Response and the relative contribution of different markets in respect of forecast error which is measured through FEVD.

9.4 Error Correction Mechanism

The error correction equation given below is normalized on CPs.

$$ECM1 = 1CPs - 0.024327CMM - 0.48983CDS - 0.70026T\text{-}bills \qquad (33)$$

The error correction term represents the deviations from the long run relationship. The signs of the coefficients CMM, CDs and T-bills rate are in line with the economic theory. The co-integrating vector suggests that CPs rate is positively related with CMM rate, CDs rate and the T-bills rate.

9.5 Vector Error Correction Model

We estimate Vector Error Correction Model, using the above error correction term as another independent variable in the unrestricted VAR model in first difference with the optimal chosen lag length equal to four. Thus, the VECM is specified as:

D (CMM) = 0.65072D (CPs(-1)) + 0.43374D (CPs(-2)) - 0.04051D (CPs(-3)) -.51441D (CMM(-1)) - 0.44824D (CMM (-2)) - 0.32883D (CMM (-3)) -0.21072D (CDs (-1)) - 0.41288D (CDs(-2)) - 0.12856D (CDs(-3)) + 0.21677D (T-bills(-1)) - 0.08551D (T-bills(-2)) + 0.44214D (T-bills(-3)) - 0.86004ECT (34)

D (CPs) = 0.08149D (CPs(-1)) + 0.30460D (CPs(-2)) + 0.28578D (CPs(-3)) -0.03951D (CMM(-1)) - 0.03173D (CMM(-2)) - 0.00343D (CMM(-3)) -0.07624D (CDs(-1)) - 0.12173D(CDs (-2)) - 0.17488D (CDs(-3)) + 0.05481D (T-bills (-1)) -0.04485D (T-bills (-2)) - 0.16882D (T-bills (-3)) - 0.57523ECT (35)

D(CDs) = 0.21521D (CPs(-1)) + 0.39201D (CPs(-2)) + 0.10345D (CPs(-3)) + 0.080821 D(CMM(-1)) + 0.00461D (CMM(-2)) + 0.02279D (CMM(-3)) -0.29723D (CDs(-1)) - 0.21333D (CDs (-2)) - 0.10273D (CDs (-3)) + 0.11650D (T-bills (-1)) + 0.13409D (T-bills (-2)) - 0.08611D (T-bills (-3)) + 0.12815ECT (36)

D (T-bills) = -0.01933D (CPs (-1)) + 0.07093D (CPs (-2)) + 0.07267D (CPs (-3)) + 0.02047D (CMM (-1)) + 0.00768D (CMM (-2)) + 0.04503D (CMM (-3)) + 0.01009D (CDs (-1)) + 0.01594D (CDs (-2)) - 0.02025D (CDs (-3)) - 0.20353D (T-bills (-1)) - 0.10174D (T-bills (-2)) - 0.02171D (T-bills (-3)) - 0.04052ECT (37)

It would be pertinent to recapitulate that we have selected a particular model of unit roots, an order of lag length four, selected one cointegrating vector and normalized on CPs. Although, we have estimated four models of VECM, we will concentrate only on the model which is normalized on CPs. In the above system, the coefficients for the speed of adjustment are -0.86004, -0.57523, 0.12815 & -0.04052 for CMM, CPs, CDs and T-bills respectively obtained from above equations 34 to 37. The negative coefficient of the Error Correction Term suggests that any deviation from the long run leads to an overshooting which is then corrected by the ECT. In the selected model, normalized on CPs, the coefficient of the ECT is (-) 0.57. This implies that within two time periods the system adjusts to the long run equilibrium since the time taken is the inverse of the coefficient of the ECT. Large value of the adjustment parameter shows the rate of interest is highly responsive to the previous period's deviation from long run equilibrium. But the relatively small values of the other coefficients suggest that the coefficients are not very responsive to previous period's deviation from equilibrium. Speed of adjustment coefficient is expressed as change per unit of time. The speed of adjustment coefficient is of particular interest in that they have important implications for the dynamics of the system. At least some of them should be significantly different from zero, if the variables are cointegrated. After all, if all adjustment coefficients are zero, there is no error correction and equations 34 to 37compromise nothing more than a VAR in first difference. The Table shows the significance of the speed of adjustment parameters **(See Table V)**.

Table V Here

The adjustment process is supported by the fact that those coefficients that are significantly different from zero are also large in magnitude and hence compensate for the low magnitude of the other markets such as T-bills and CDs market. The short run adjustments are therefore largely carried out through CMM and CPs. T-bills which were at one time seen as having the potential for being a central market or as a reference rate are not being supported as far as the ECM is concerned. They would not have the required speed of correcting the money market. This is partly because T-bills have a longer holding period in comparison to CMM. Since CMM has a shortest holding period it is best suited for affecting the short term adjustment.

9.6 Diagnostics Tests

9.6.1 Jarque Bera Test for Testing Normality

Having found that all the variables are I (1), we carried the test for normality on the residuals of the differenced series. From the table, we find that none of the null hypothesis is accepted. Thus, we can conclude that none of the residuals of the series is normally distributed. This is not according to the model testing requirements.

This could be true because of two factors. One that the VAR equation consists of both the slow moving and fast moving markets like T-bills and Call Money Market simultaneously. Second, on account of some volatility persistence, which could not be tested for due to lack of time and space **(See Table VI).**

Table VI Here

9.6.2 Serial Correlation Test

After selecting the order of VAR, it is prudent to check the residuals of individual equations for serial correlation. The LM statistic given by (T-p) R^2 is compared with critical value 3.84 (χ^2) with 1 degree of freedom. Since the calculated value for all the series with lag length 4 (p) is less than the critical value, at 5 percent significance level, we do not reject the null of no serial correlation **(See Table VII).**

Table VII Here

9.6.3 Cusum Test

From figure 1 we find that the cumulative sum of recursive residuals for commercial paper lie within the 5 percent critical bound limit. Similarly, in other three markets also we find that the cumulative sum of recursive residuals is going along the central line. There is not much variance implying that the parameters are stable **(See Figure 1).**

Figure 1 Here

9.7 Granger Causality Test

Using the vector error correction model, we test whether the variables individually Granger cause other variables or not. For this, we test for the joint significance of the lagged variables of each variable along with the error correction term. The results reported in Table VIII indicate that the null hypothesis of no Granger causality is strongly rejected in all the cases except in the case between CPs and CDs where the relationship is not so strong **(See Table VIII).**

Table VIII Here

F-test is performed to check Granger causality. The first column gives the null hypothesis of no causality between the variables; the second column gives the number of lags whereas the third column gives the chi-square statistic and the p-values in parenthesis. The conclusion is given in column four.

This test shows that there is no single market, which is not caused by the other market. At best there are two markets, that is, CPs and CDs, which have weak causality. Nevertheless, in a bilateral framework bi way causality is established in all cases

9.9 Dynamics of Money Market Efficiency

We have already demonstrated that our money market is networked. It now needs to be seen as to what is the nature of the dynamics of this vital market. The hallmark of dynamic efficiency lies in the ability of markets to respond to shocks. An efficient market upon receiving a shock stabilizes and reaches a path of stability in a short period of time. Secondly, such markets should allow for reasonably good forecasts. This implies that the forecast error should be minimized and it should be possible to identify the source of forecast error. For this we have carried out two sets of empirical tests:

1) Impulse response; and
2) Forecast error variance decomposition.

An investigation of the dynamic interaction of various shocks in the post sample period is examined using impulse response functions and variance decomposition. Ordinarily a generalized impulse response function is used for testing for shocks on the various markets. Since our markets are networked shocks are likely to be contemporaneous in which case the results of orthogonalised impulse response and generalized impulse response functions may be different. The advantage of using the generalized impulse responses is that the orthogonalised impulse responses and variance decompositions depend on the ordering of the variables. If the shocks to the respective equations in VAR are contemporaneously correlated, the orthogonalised and generalized impulse responses may be quite different. On the other hand, if shocks are not contemporaneously correlated, then the two types of impulse responses may not be that different and also orthogonalised impulse responses may not be sensitive to a re-ordering of the variables. The purpose of the former is to study the specific effects and the latter is to study the general effects of the shocks on the system.

9.9.1 Impulse Response Function

Thus, the impulse response analysis is used to analyze the dynamic relationship among variables. They indicate the direction (positive or negative) and the nature (temporary or permanent) of the variation.

The graphs show the impulse response relationship amongst various variables. For testing the impulse response we give a one standard deviation shock to each variable arising from an own innovation or from an innovation from another market. We observe four phenomena as a response:

1) The direction of change;
2) The quantum of change;
3) The time period; and
4) Time for stabilization.

All the impulses are positive, that is, there is a perceptible sudden rise in the interest rate. There are some short run fluctuations which vary between markets and most of the markets stabilize in the long run around 5 to 10 month time horizon. The concerned market neither does nor reverts to the initial level because what is being observed is the isolated effect of the impulse generated by one market on another market individually. Whereas, our system is a multivariate VAR which is likely to converge only by the simultaneous affect of all other markets. Further more each variable has a basic level of volatility that can be expressed as the inherent value of its own standard deviation. Therefore, the process of stabilization brings the variable back to level of its natural standard deviation. Even in the case of cointegrated markets it cannot be expected that the standard deviation would reduce to near zero levels because cointegration implies long run stability amongst non stationary variables and not stationary variables. It is only in the case of stationary variable that the standard deviation over time would be constant.

Impulse responses for CPs show that in all the three graphs, the directions of changes observed in the impulse responses conform to the signs obtained earlier in the cointegrating vector. The immediate and permanent effect on CPs of a one standard deviation shock to CMM is positive. There is an initial dip to 0.3 around 3-month time horizon followed by some short run fluctuations and then it stabilizes around 8-month time horizon **(See Figures 2 to 4).**

Figures 2 to 4 Here

The net impact of a one standard deviation shock to the CDs rate is positive. It exhibits a rising trend, reaches 0.7 and then it dips at around 3-month time horizon and eventually stabilizes at around 7 month time horizon.

A one standard deviation shock to T-bills has a positive impact on CPs. It exhibits a rising trend initially and reaches 0.28 and then dips for a short time horizon, after which it stabilizes at around 7 month time horizon.

Impulse responses for CMM show that in all the three graphs, the directions of changes observed in the impulse responses also conform to the signs obtained earlier in the cointegrating vector. Impulse responses for CMM show that the immediate and permanent effect of a one standard deviation shock to CD is positive **(See Figures 5 to 7).**

Figures 5 to 7 Here

It rises in the short run to 0.6, fluctuates slightly and then it stabilizes fast at around 12 month time horizon. A one standard deviation shock to CPs has a positive effect, it rises initially to 0.5 and then at around 8-month time horizon it stabilizes. A one standard deviation shock to T-bills has a positive effect, at around 4-time horizon there is a positive jump to 0.45, and then it fluctuates for a while and stabilizes around 8 month time horizon.

Impulse responses for CDs also show that in all the three graphs, the directions of changes observed in the impulse responses also conform to the signs obtained earlier in the cointegrating vector **(See Figures 8 to 10).**

Figures 8 to 10 Here

A one standard deviation shock to CPs has a positive effect, it rises initially and reaches 0.4 and then at around 8-month time horizon it stabilizes. The net impact of a one standard deviation shock to CMM is positive. There is a dip initially to 0.2 but in a very short period it recovers and rises and reaches 0.8 and then stabilizes fast.

The effect on CDs of a one standard deviation shock to T-bills is positive. It rises initially to 0.15, then falls, rises again quite acutely and then stabilizes around 9-month time horizon.

Impulse responses for T-bills also exhibit a similar trend **(See Figures 11 to 13).**

Figures 11 to 13 Here

A one standard deviation shock to CPs has a positive effect, it rises initially and reaches 0.6 and then it stabilizes around 7-month time horizon. A one standard deviation shock to CMM has a long run positive impact on T-bills, though it dips quite acutely in the beginning to as low as 0.1, then rises and stabilizes fast around 10 month time horizon. The immediate and permanent effect of a one standard deviation shock to CDs is positive and smooth. It rises in the beginning, reaches 0.5, and then stabilizes.

9.9.2 Forecast Error Variance Decomposition

Variance decompositions give the proportion of the h-periods-ahead of a variable that can be attributed to another variable. The more the unexplained part is explained by a particular market, the more it is taking the system away from a perfect forecast.

From Table XII, we find that at the end of the 40-month forecast horizon, CMM rate explain about 27 percent of the total variation in forecast error in T-bills, whereas from Table X, we find that T-bills explain about 26 percent of the total variation in forecast error in CMM. These results reinforce the bi-directionality between T-bills rate and CMM rate as was indicated in the Granger Causality tests and impulse response functions (**See Tables X and XII).**

Tables X and XII Here

The CMM plays an important role in determining the forecast error variance of CDs and CPs in generalized FEVD, whereas only 11 percent of the forecast error variance of CMM is explained by CDs (**See Tables IX and X).**

Tables IX and X Here

Similarly, only 2 percent of the forecast error variance of CMM is explained by CPs in case of generalized FEVD. This shows that CMM is an important market in determining the forecast error variance in the other markets, whereas other markets are not important in determining the forecast error variance of CMM except T-bills in case of explaining forecast error variance of CMM . Around 60 percent of the forecast error variance of CMM is explained by its own innovations.

The T-bills market determines around 32 percent and 23 percent of the forecast error variance in CPs **(See Table IX).**

Table IX Here

T-bills market also determines around 12 percent of forecast error variance in CDs and 26 percent of forecast error variance of CMM in case of generalized FEVD. This shows that T-bills are an important variable in determining forecast error variance of other markets.

CDs do play a role in determining forecast error variance of CPs, whereas it does not play much role in determining forecast error variance of CMM and T-bills **(See Tables IX, X and XII).**

Tables IX, X and XII Here

Similarly, CPs play a role in determining forecast error variance of CDs, whereas it does not play much role in determining forecast error variance of CMM and T-bills.. Only 2 percent of the forecast error variance of CMM is explained by CPs.

Effects on CPs

From Table IX, we find that at the end of the 40-monthly forecast horizon, around 13 percent of the forecast error variance of CPs is explained by its own innovations. Call money market rates explain about 27 percent of the total variation in forecast error after 40 months. Around 32 percent of the forecast error is explained by the treasury bills rate and the rest explain variance of CPs by the CDs rates. Thus, the determinants of forecast error variance of CPs in descending order of importance include the treasury bills rate, the call money rates and the certificate of deposit rates **(See Table IX).**

Table IX Here

Effects on CMM

From Table X, we find that at the end of the 40-month forecast horizon, around 60 percent of the forecast error variance of CMM is explained by its own innovations. Treasury bills rates explain about 26 percent of the total variation in forecast error after 40 months. Around 13 percent of the forecast error is explained by the CPs rate and the CDs rates taken together. Thus, the determinants of forecast error variance of CMM in descending order of importance include the treasury bills rate, the CPs rates and the certificate of deposits rates **(See Table X).**

Table X Here

Effects on CDs

From Table XI, we find that at the end of the 40-month forecast horizon, around 51 percent of the forecast error variance of CDs is explained by its own innovations. Treasury bills rates explain about 12 percent of the total variation after 40 months. Around 14 percent of the forecast error is explained by the CPs rate and the rest, that is, around 21 percent by the CMM rates **(See Table XI).**

Table XI Here

Effects on T-bills

Lastly, from Table XII, we find that at the end of the 40-month forecast horizon, around 60 percent of the forecast error variance of T-bills is explained by its own innovations. CMM rate explain about 27 percent of the total variation in forecast error after 40 months. These results reinforce the bi-directionality between T-bills rate and CMM rate as was indicated in the Granger Causality tests and impulse response functions. Around 11 percent of the forecast error is explained by the CPs rate and the CDs rates taken together. Thus, the determinants of forecast error variance of T-bills in descending order of importance include the CMM rate, the CPs rates and the certificate of deposits rates **(See Table XII).**

Table XII Here

10 Hypotheses Testing

In the beginning of the paper we have laid out a set of primary and secondary hypotheses. The above analysis has clarified how the primary and secondary hypotheses have been tested with the help of appropriate methodologies and statistical tools. We now present the hypotheses along with conclusions thereof.

10.1 Primary Hypotheses

A primary hypothesis is that with the given conditions of financial liberalization the money market has responded by behaving in an efficient manner in the long run.

The following is the list of secondary hypotheses which we have tested in the paper. The results are as follows.

10.2 Secondary Hypotheses

10.2.1 The interest rates should stabilize in the long run.

With the evolution of more generalized methods of estimation such as the multivariate Vector Auto Regressive framework, we have carried out tests for more complex structures of market integration, that is, we have tested for long term market integration. On the whole equation (33) tells us that the Indian Money Market is efficient in the long run in an overall sense whereas the role and significance of different markets vary amongst each other.

10.2.2 The relationship between long run stability and short run stability is efficient.

This has been tested for using Vector Error Correction Model. The error correction term represents the deviations from the long run relationship amongst the four variables. The signs of the coefficients CMM, CDs and T-bills rate are in line with the economic theory. However, the results are mixed because it was found that some of the speeds of adjustment coefficients were significantly different from zero which further strengthens our results that the variables are cointegrated. The coefficient of the Speed of Adjustment parameters from for CPs and CMM are significant while they are not significant for other sub markets. In net, we can conclude that the process of short run and long run adjustment is not entirely efficient.

10.2.3 Shocks to any one of the sub markets would be transmitted to other sub markets and would be absorbed without persistence.

This hypothesis has also been tested for by using the impulse response function. There are some short run fluctuations which vary between markets and most of the markets stabilize in the long run around 10 month time horizon. The hypothesis is largely accepted.

10.2.4 The impact of one sub market on the other differs in degree.

This hypothesis is tested for using Forecast Error Variance Decomposition analysis. In general the degree of impact differs between sub markets. It shows that CMM is an important market in determining the forecast error variance in the other markets; whereas other markets are not important in determining the forecast error variance of CMM except T-bills in case of explaining forecast error variance of CMM in generalized FEVD.

10.2.5 There is a causal dynamic bilateral relationship amongst the sub-markets.

We have tested whether the variables individually Granger cause other variables or not. This is only a necessary condition for the further tests that are being conducted for understanding the structure of market integration. The hypothesis is confirmed strongly in all cases except one.

11 Policy Recommendations

11.1 Long Run Efficiency

Through a multivariate VAR framework, we find that CMM is weak in terms of long run relationship, that is, it is not helping in long run stabilization. CMM plays a role in short term adjustments. The whole talk of CMM being a potential reference rate or a central market does not seem to hold good. T-bills particularly is weak in the short term adjustment process. Therefore, on the whole in any case, it rules out any single reference rate or central market.

While all other markets are strong in terms of long run relationship, the T-bills market is the strongest.

The policy implication is that for the development of the money market we need a combination of CMM and T-bills. Clearly the reliance on any single reference rate or central market is not likely to produce the desired long term development and stability.

11.2 Relationship between Short Run and Long Run

We find that the coefficient of the Speed of Adjustment parameters for CPs and CMM are significant, implying that in case of deviation from long-run equilibrium, the entire burden of adjustment falls on commercial paper and call money market. Since CMM has a shortest holding period it is best suited for affecting the short term adjustment. T-bills which were at one time seen as having the potential for being a central market or as a reference rate are not being supported as far as the ECM is concerned. They would not have the required speed of correcting the money market. This is partly because T-bills have a longer holding period in comparison to CMM. CMM is responsible for short term adjustment, whereas T-bills are not so effective in short term adjustment. On the other hand the CMM is not strongly influencing the long term relationship in the money market, whereas T-bills market is responsible for long term equilibrium and stationarity. Therefore, the T-bills set the tone for the long term development of the money market. They should continue to be viewed as a means for long term stabilization. The policy implication is that the monetary authorities should rely on CPs and CMM for short run adjustments.

From the above results there are three vital policy implications.

i) No single market can be isolated for policy treatment;

ii) Generalized policy measures need to be evolved; and

iii) Policy makers must recognize and must be sensitized to the fact that they are dealing with a more evolved money market.

12 Summary and Conclusions

From the empirical estimates above we conclude that a long run cointegrating vector exists. There is a single vector which follows the theory. We have established that there is long run market efficiency in an overall sense through multivariate VAR framework. We have shown that at least some of the markets show adjustment between short run and long run on account of the ECM. Also our results show that there is an integral relationship amongst sub markets which make them respond to shocks emanating from other markets through the IRF. We can also conclude that each of the markets has a specific effect in terms of the error components through the FEVD.

It was found after looking at the results of our cointegration analysis that the cointegrating vector arrived at shows that the nature of the relationship is positive and this long term relationship has the desirable effect of co movement in rates of interest. The results show that the T-bills play a major role in stabilizing the market in the long run since its impact is the greatest. Next in that order, CDs play a vital role while call money market which is a relatively volatile market plays a minor role in the stabilization of long term market interest rates. This is corroborated by the significance level in which case it is apparent that call money market alone is a market which is not highly significant. On the whole the above equation tells us that the Indian Money Market is efficient in the long run in an overall sense whereas the role of different markets vary amongst each other. There is a policy relevance to it. The policy makers have to rely on T-bills for long term development of an efficient money market.

Looking at the Vector Error Correction Model we know that the coefficients of the Speed of Adjustment parameters for CPs and CMM are significant while they are not significant for other sub markets. This implies that in case of deviation from long-run equilibrium, the entire burden of adjustment falls on commercial paper and call money market, that is, the policy makers have to rely on CMM primarily for making dynamic adjustments between short and long run. The results of Granger causality indicate that the null hypothesis of no Granger causality is strongly rejected in all the cases except in the case between CPs and CDs where the relationship is not so strong.

The above results have some implications for the policy makers. They have to take note of the variance decomposition in determining the particular variable that needs to be monitored so as to understand the timing of such a policy. We found that the most dominant variable was CMM. With the finding that we have networked market structure the monetary authorities need to be sensitive to a new paradigm of monetary management. They cannot rely upon a single instrument such as open market operations.

Table I: Order of VAR Test

Lag	AIC	SBC	Adjusted LR (p-value)
1	-981.947	-1019.7*	160.6299[.002]
2	-986.402	-1049.4	142.1053[.002]
3	-989.974	-1078.1	122.1616[.002]
4	-980.960*	-1095.3	83.6276[.061]*
5	-982.290	-1120.8	58.4825[.143]
6	-990.249	-1153.9	45.5799[.057]
7	-993.775	-1182.6	25.5640[.060]
8	-993.844	-1207.9	N.A

*Indicates lag order selected by the criterion

LR: sequential modified LR test statistic (each test at 5 percent level), values in parenthesis are p-values.

AIC: Akaike Information Criterion

SBC: Schwartz Bayesian Criterion

Table II: Testing for Rank of VAR: λ_{max} and λ_{trace} Tests

H_0:	**H_1:**	**Statistics**	**Critical Values**		**Results**	**No. of C.V.**
			95 percent	**90 percent**		
λ_{max} tests						
r = 0	**r = 1**	41.38	23.92	21.58	Reject Null Hypothesis	2
r ≤ 1	**r = 2**	28.32	17.68	15.57	Reject Null Hypothesis	
r <=2	**r=3**	9.10	11.03	9.28	Do not reject Null Hypothesis	
H_0:	**H_1:**	**Statistics**	**Critical Values**		**Results**	**No. of C.V.**
			95 percent	**90 percent**		
λ_{trace}						
r = 0	**r>=1**	81.9439	39.81	36.69	Reject Null Hypothesis	2
r ≤ 1	**r>=2**	40.5620	24.05	21.46	Reject Null Hypothesis	
r <=2	**r>=3**	10.15	12.36	10.25	Do not reject Null Hypothesis	

Note:

i) r is the rank of VAR.

ii) C. V. denotes the cointegrating vector.

Table III: Estimate of Cointegrating Vectors

Estimated Cointegrated Vectors in Johansen Estimation (Normalized in Brackets)

Cointegration with no intercepts or trends in the VAR

	Vector 1	**Vector 2**
CPs	.136(-1.000)	.002(-1.000)
CMM	-.003(.024)	-.047(16.203)
CDs	-.066(.489)	-.020(6.953)
T-bills	-.095(.700)	.068 (-23.493)

Table IV: Zero-Restriction Test

Null Hypothesis	χ^2 (Calculated)	Conclusion
CMM=0	.065 [.799]	Do not reject null hypothesis
CDs=0	11.56 [.001]	Reject null hypothesis*
T-bills=0	8.64 [.003]	Reject null hypothesis*

Note: p value in parenthesis

* indicates at 5 percent level of significance.

Table V: Significance of the Speed of Adjustment Parameters

Test Variable	**Null Hypothesis**	**Coefficient**	**t-statistic Calculated**	**Results**
CMM	$\alpha_{cmm} = 0$	-0.86004	-2.3015[.023]	Reject null hypothesis*
CPs	$\alpha_{CPs} = 0$	-0.57523	-5.3948[.000]	Reject null hypothesis*
CDs	$\alpha_{cds} = 0$	0.12815	.883[.378]	Do not reject null hypothesis
T-bills	$\alpha_{T\text{-}bills} = 0$	-0.04052	-.50887[.612]	Do not reject null hypothesis

Note: p value in parenthesis

* indicates at 5 percent level of significance.

Table VI: Test for Normality of Residuals

Null Hypothesis	**χ^2 Statistic Calculated at 2 degrees of freedom**	**Results**
CPs is normally distributed	11.2444[.004]	Reject null hypothesis*
CMM is normally distributed	1178.0[.000]	Reject null hypothesis*
CDs is normally distributed	1178.0[.000]	Reject null hypothesis*
T-bills is normally distributed	97.8219[.000]	Reject null hypothesis*

* indicates at 5 percent level of significance.

Table VII: Test for Serial Correlation in Residuals

Variables	**LM Test Statistic**
CMM	19.1800[.084]
CPs	26.3524[.070)
CDs	19.3673[.080]
T-bills	12.3351[.419]

Table VIII: Granger Causality Tests

Null Hypothesis	**Number of Lags**	χ^2 **(Calculated)**	**Conclusion**
CPs is not Granger caused by CMM rate	3	40.97[.001]	Reject null hypothesis*
CPs is not Granger caused by CDs rate	3	22.89[.117]	Reject null hypothesis**
CPs is not Granger caused by T-bills rate	3	54.78[.000]	Reject null hypothesis*

CMM is not Granger caused by CPs	3	40.97[.001]	Reject null hypothesis*
CMM is not Granger caused by CDs	3	44.07[.000]	Reject null hypothesis*
CMM is not Granger caused by T-bills	3	59.19[.00]	Reject null hypothesis*
CDs is not Granger caused by CPs	3	22.89[.117]	Reject null hypothesis**
CDs is not Granger caused by CMM	3	44.07[.000]	Reject null hypothesis*
CDs is not Granger caused by T-bills	3	60.39[.000]	Reject null hypothesis*
T-bills is not Granger caused by CPs	3	54.78[.000]	Reject null hypothesis*
T-bills is not Granger caused by CMM	3	63.06[.000]	Reject null hypothesis*
T-bills is not Granger caused by CDs	3	60.39[.000]	Reject null hypothesis*

Note: p value in parenthesis.

*, **, at 5 percent and 15 percent level of significance respectively

Table IX: Generalized Forecast Error Variance Decomposition for Commercial Paper

Horizon	CPs	CMM	CDs	T-bills
0	0.716363	0.109611	0.077682	0.096344
1	0.507188	0.185262	0.129803	0.177748
8	0.237286	0.248623	0.224431	0.289661
16	0.17121	0.267423	0.250598	0.310769
22	0.15384	0.272322	0.257383	0.316455
28	0.143842	0.275135	0.261292	0.319731
36	0.13568	0.27743	0.264484	0.322405
40	0.132817	0.278236	0.265606	0.323341

* See note below

Table X: Generalized Forecast Error Variance Decomposition for Call Money Market

Horizon	CPs	CMM	CDs	T-bills
0	0.097994	0.640443	0.081881	0.179683
1	0.091581	0.626981	0.092042	0.189396
8	0.044852	0.611499	0.104353	0.239297
16	0.031473	0.608201	0.108814	0.251511
22	0.026976	0.607059	0.110195	0.255771
28	0.024211	0.606347	0.111022	0.258419
36	0.021839	0.605738	0.111734	0.26069
40	0.020982	0.605519	0.11199	0.261509

*See note below

Table XI: Generalized Forecast Error Variance Decomposition for Certificates of Deposit

Horizon	**CPs**	**CMM**	**CDs**	**T-bills**
0	0.086583	0.102081	0.798445	0.012891
1	0.159189	0.161987	0.638613	0.040211
8	0.184101	0.197402	0.515691	0.102807
16	0.158008	0.209282	0.517441	0.115269
22	0.151464	0.212341	0.517561	0.118634
28	0.147642	0.21412	0.517652	0.120586
36	0.144511	0.215579	0.517723	0.122187
40	0.14341	0.21609	0.517747	0.122753

*See note below

Table XII: Generalized Forecast Error Variance Decomposition for Treasury Bills

Horizon	CPs	CMM	CDs	T-bills
0	0.09397	0.196032	0.011281	0.698717
1	0.083528	0.218717	0.017553	0.680203
8	0.085749	0.260408	0.040386	0.613457
16	0.075196	0.267296	0.046338	0.611171
22	0.072526	0.269235	0.047935	0.610304
28	0.070964	0.270369	0.048867	0.609799
36	0.06969	0.271297	0.049632	0.609381
40	0.069243	0.271624	0.049901	0.609232

*See note below

*Note: Entries in each row are the proportion of the variances of the forecast error in the case of each variable that is being measured. This can be attributed to each of the variables indicated in the column headings. The decompositions are reported for zero, one, eight, sixteen, twenty two, twenty-eight, thirty-six and forty monthly horizons. Both the generalized and the orthogonalized error variance decompositions add up to one since it has been normalized (However, due to rounding off there may be minor differences in certain cases).

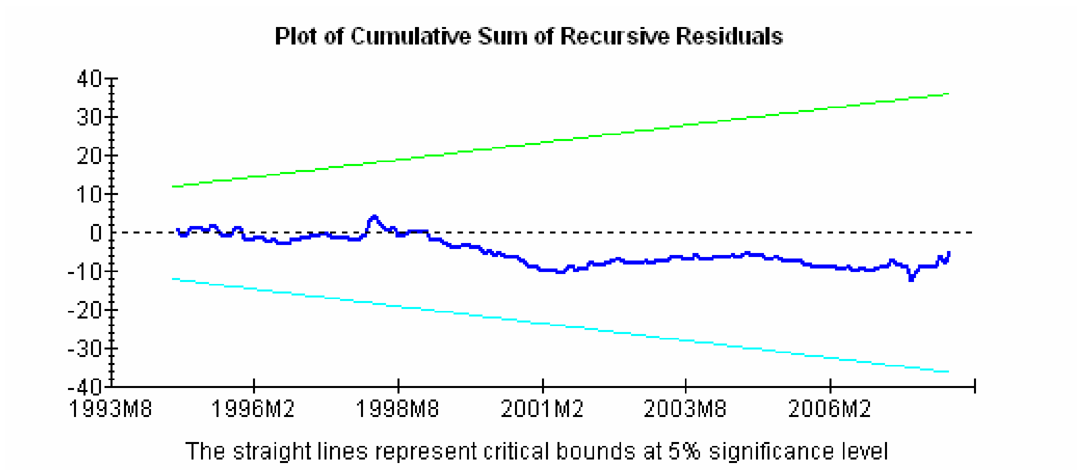

Figure 1: Cusum Test on Residuals of Commercial Paper

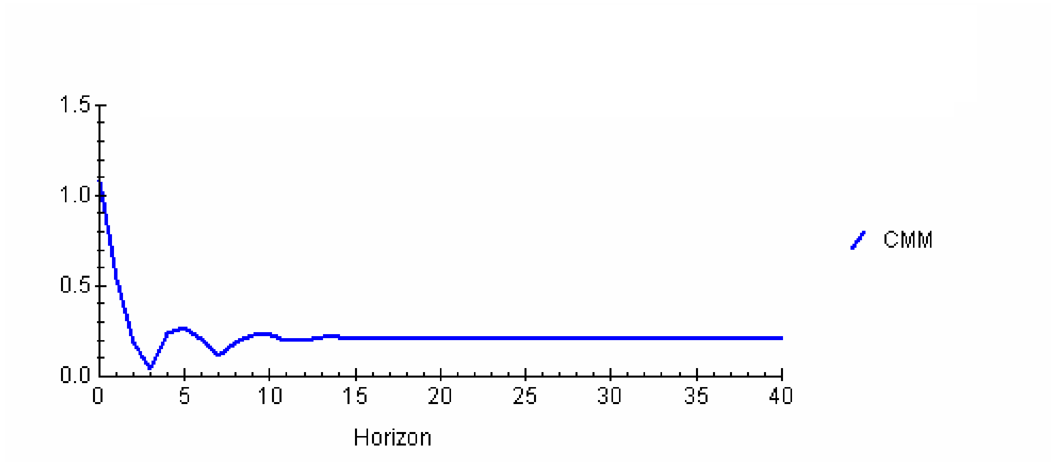

Figure 2: **Generalized Impulse Response to one S.E. Shock in Call Money Market in the Equation for Commercial Paper**

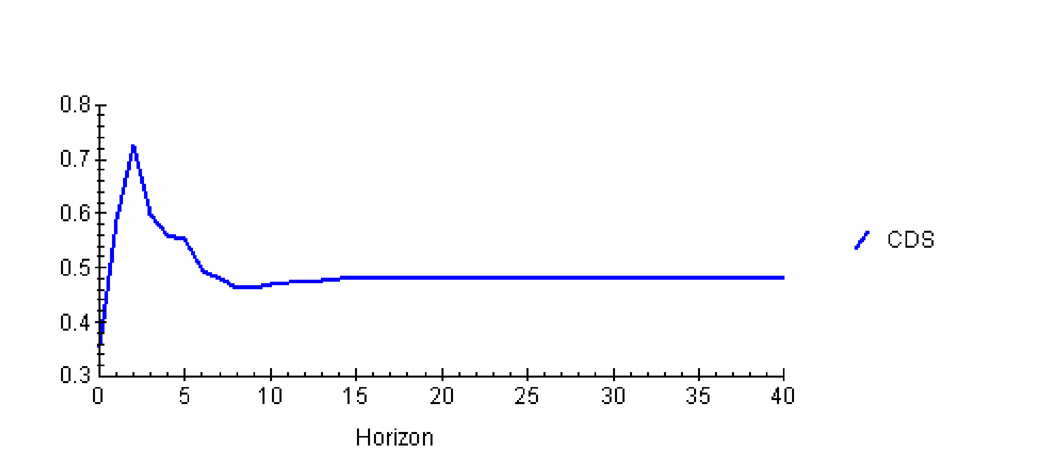

Figure 3: Generalized Impulse Response to one S.E. Shock in Certificates of Deposit in the Equation for Commercial Paper

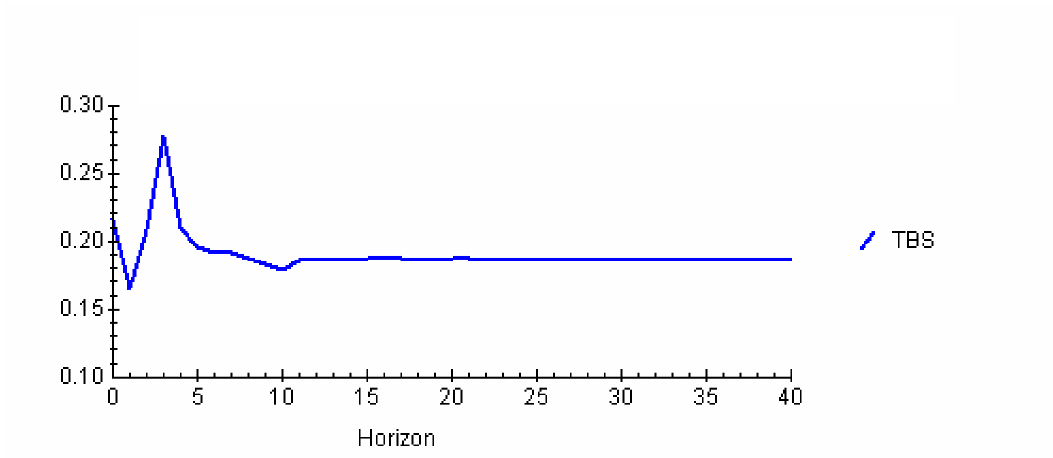

Figure 4: Generalized Impulse Response to one S.E. Shock in Treasury Bills in the Equation for Commercial Paper

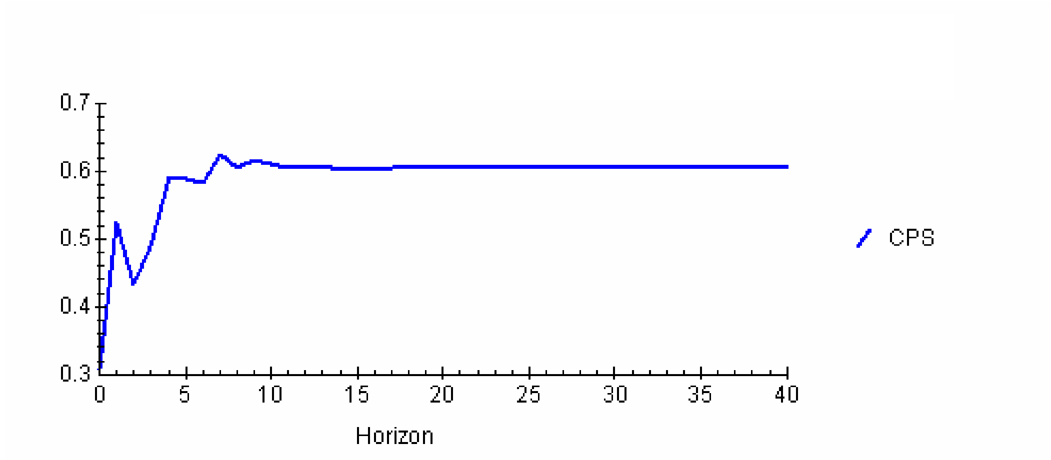

Figure 5: Generalized Impulse Response to one S.E. Shock in Commercial Paper in the Equation for Call Money Market

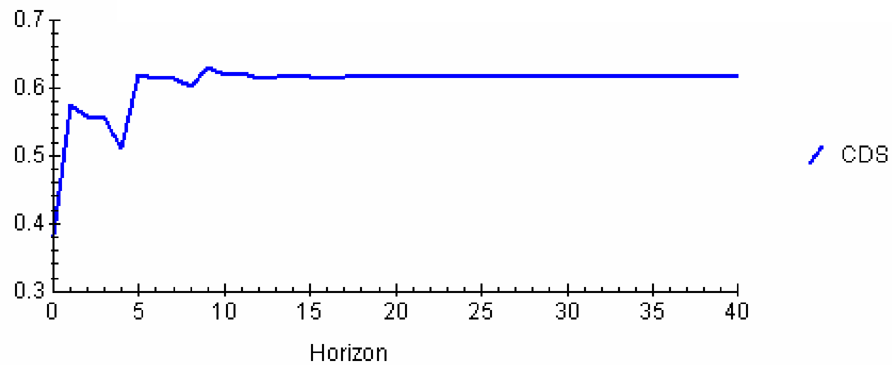

Figure 6: Generalized Impulse Response to one S.E. Shock in Certificates of Deposit in the Equation for Call Money Market

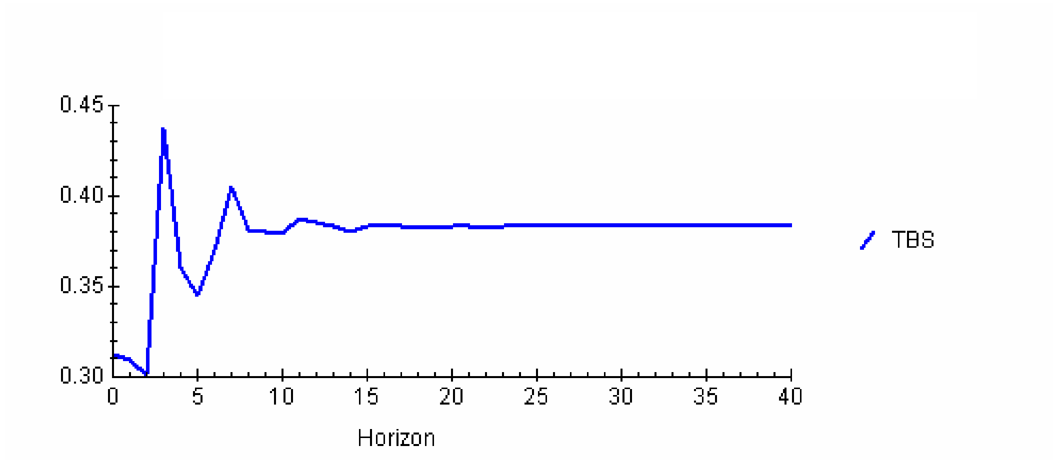

Figure 7: Generalized Impulse Response to one S.E. Shock in Treasury Bills in the Equation for Call Money Market

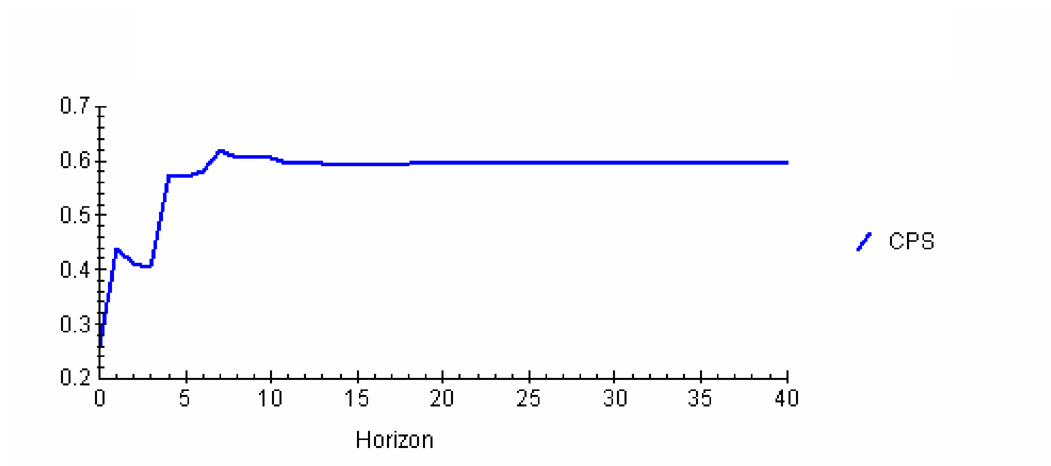

Figure 8: Generalized Impulse Response to one S.E. Shock in Commercial Paper in the Equation for Certificates of Deposit

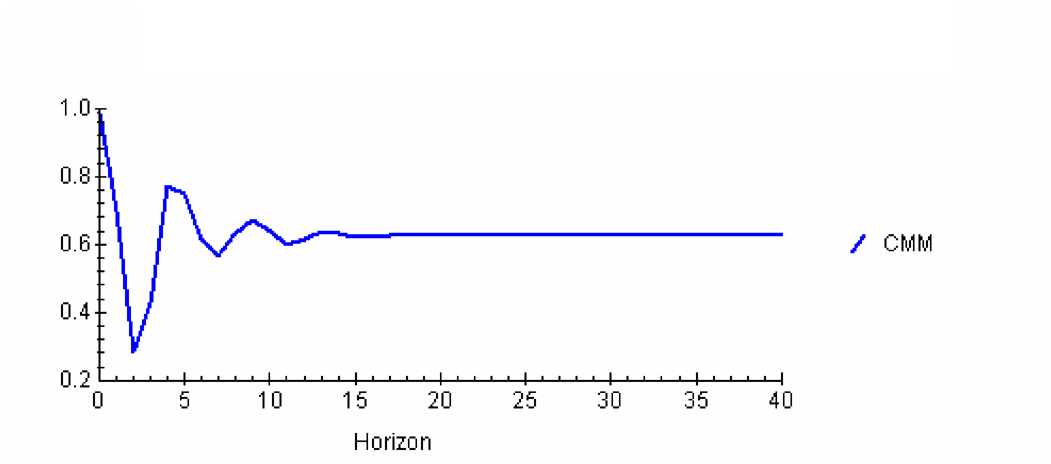

Figure 9: Generalized Impulse Response to one S.E. Shock in Call Money Market in the Equation for Certificates of Deposit

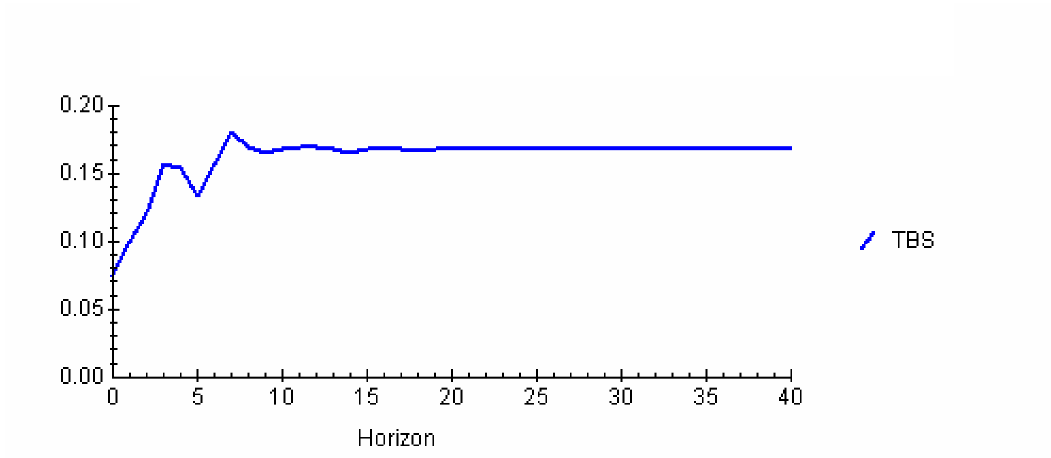

Figure 10: Generalized Impulse Response to one S.E. Shock in Treasury Bills in the Equation for Certificates of Deposit

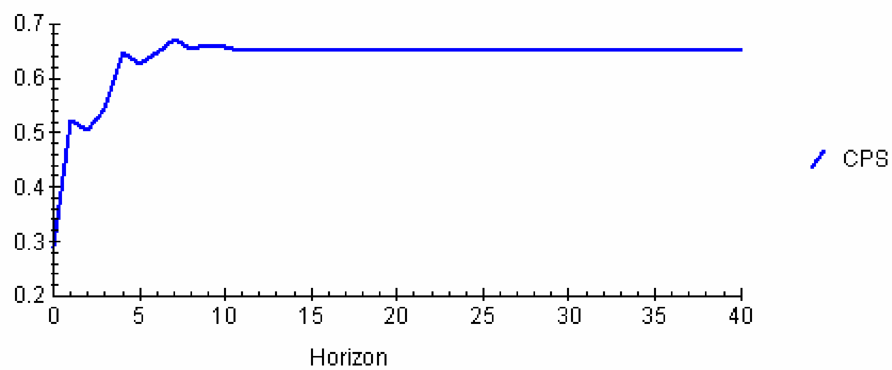

Figure 11: Generalized Impulse Response to one S.E. Shock in Commercial Paper in the Equation for Treasury Bills

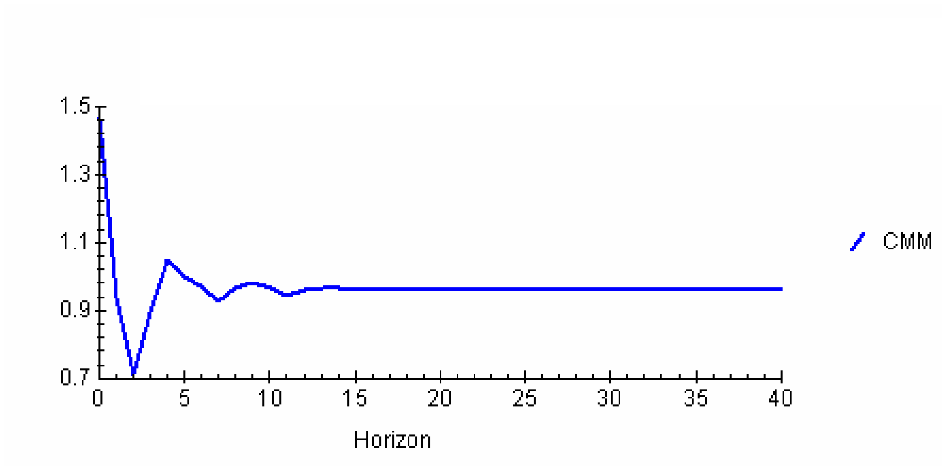

Figure 12: Generalized Impulse Response to one S.E. Shock in Call Money Market in the Equation for Treasury Bills

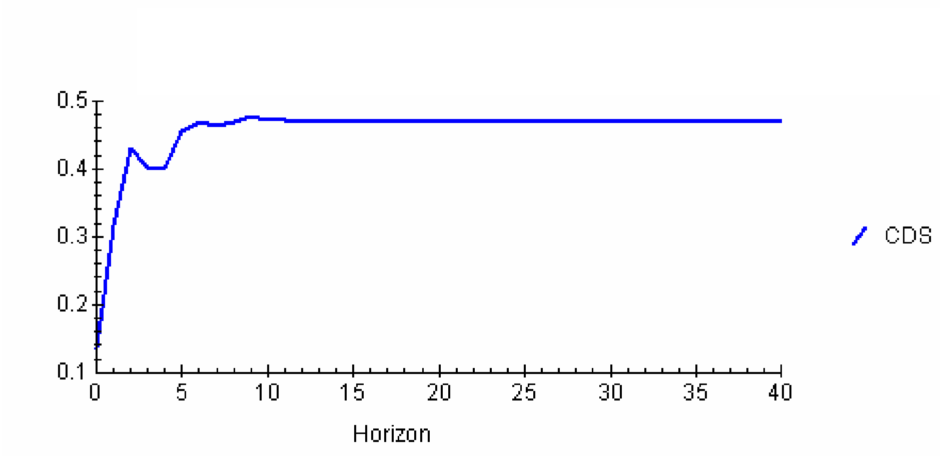

Figure 13: Generalized Impulse Response to one S.E. Shock in Certificates of Deposit in the Equation for Treasury Bills

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[i] Murthy and Goel (2009). Financial liberalization and market efficiency: Testing for market integration of the money market in India. First international conference on Time series and applied econometrics held at IBS, Hyderabad.

[ii] It would be obvious that fundamentals of share cannot change so frequently as to cause such volatility in prices. Infact, there is a definite theory by Shiller which prescribes the extent to which price volatility can take place in relation to the fundamental values.

[iii] External commercial borrowings have minimum average maturity of the borrowing of three to five years. Therefore, they do not qualify as short term credit.

[iv] In the formulation of the equation the intercept is not represented because the chosen model does not have trend or intercept.

[v] For a detailed discussion and proofs, see Pesaran and Pesaran (1997) and Pesaran and Shin (1998).

Bio-sketch

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Social Science Research Network Library (SSRN) has rated twelve of his papers in the **TOP TEN LIST in the world**. His **overall ranking** at **SSRN** (amongst 121,000 economists, in the world) is at the **98 percentile.**

Bio-sketch

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