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The Dynamics of Money Velocity, External Sectors and Electronic Transactions in India: Connecting dots using Empirical Approach

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Abstract
The article presents a study to understand the behavior of money velocity for different money stock measures in India for the period 1982 – 2012 along with the important factors by which they get influenced. The first part checks the random walk hypothesis for money velocity fluctuations. The results show that the velocities do not exhibit random walk behavior which proved to be useful for analysis of money velocity dynamics. The causality tests show that the recent developments in electronic transactions are yet to have an impact on money velocity. The last part analyzes the impact of external sectors which includes the trade, the debt inflows, remittances from abroad, investments in India and the interventions from Reserve Bank of India on money velocity suitably in a VAR (1) framework and responses of the variables in future to shocks in the other variables at present have been analyzed using impulse response functions.

Jel code: C220, C530, E510, E520, E470, E170

Keywords: *Money Velocity, Money stock measures, Granger Causality, VAR*

1. Introduction

Velocity circulation of money is the ratio of the level of aggregate expenditure at current market prices in the economy to the average money stock in a given year which is actually the speed at which the money changes hands in a given financial year. Following quantity theory of money [1], the velocity is measured as a ratio of nominal GDP of a country's total supply of money. The standard monetary measures used in India are based on RBI guidelines [2] are M1: Currency with the Public + Deposit Money of the Public, $M2$: $M1$ + Post Office Saving Bank Deposits, $M3$: $M2$ + Time Deposits with Banks and $M4$: $M2$ + Total Post Office Deposits. Corresponding to each measure, four money velocities are defined as V_1, V_2, V_3 and V_4 for a given time period. It can be observed from Fig. 1 that the amount of all money stock measures has been increasing with time. However from Fig. 2, the trends in money velocity fluctuations for V_2 are similar to V_1 and V_4 are similar to V_3.

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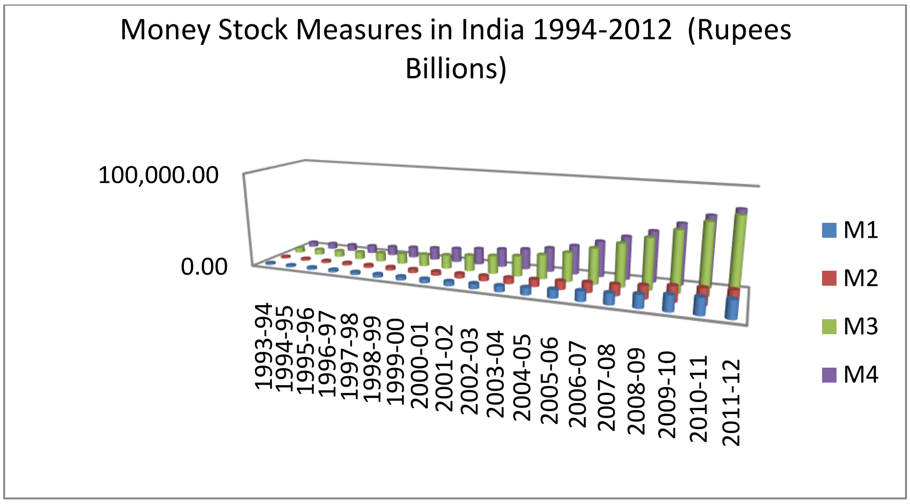

Figure 1. Variation of Different Money Stock Measures

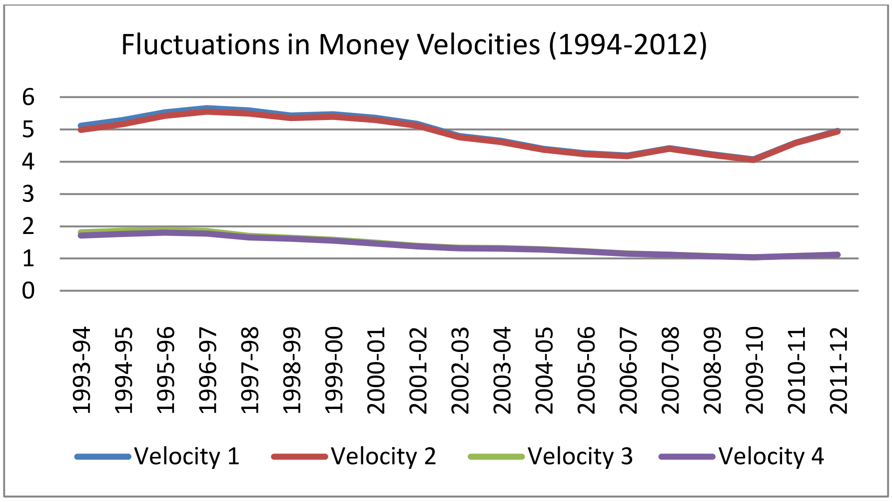

Figure 2. Fluctuations in money velocities

In this article, among several factors that affect money velocity, a detailed investigation has been done on two potential factors - volume of electronic transactions and total amount of external sectors. In the past decade there has been a phenomenal development in the volume of electronic transactions worldwide. The rapid proliferation of cards in the past 10-15 years has changed how consumers pay for goods and services, and how merchants manage their businesses. According to the 2009 -10 annual report of RBI a total of 35% transactions were done electronically, that includes cards, RTGS, NEFT [17] etc. Since the electronic transactions are mostly high value ones, this contributed to 88% in value. Fig. 3 shows the quarterly development of Electronic Retail Clearing and various kinds of electronic cards during 2004 - 2012.

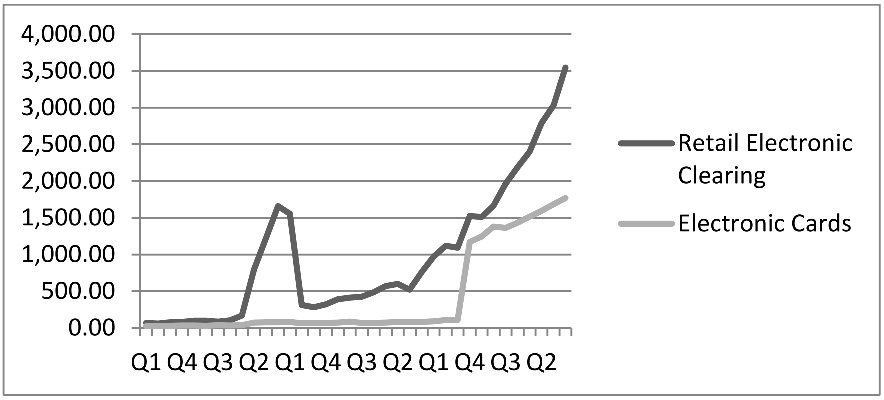

Figure 3: Development of Retail Electronic clearing & Electronic cards during 2004 - 2012

External sectors contain a basket of economic measures for any country. The important measures for India's external sector include balance of payments, foreign direct investment, portfolio investments, external debt, remittances and international aid. Besides these measures, sometimes the intervention by Reserve Bank of India which involves purchase of foreign currency from market or release (sale) of foreign currency in the market, to bring stability in exchange rates contributes to money supply. Fig. 4 gives the net external sector (in Rupees Billions) of India over the period 1994 - 2012. The values are constantly negative owing to India's high negative values of trade balance. The plot also shows the net amount of RBI interventions during the period.

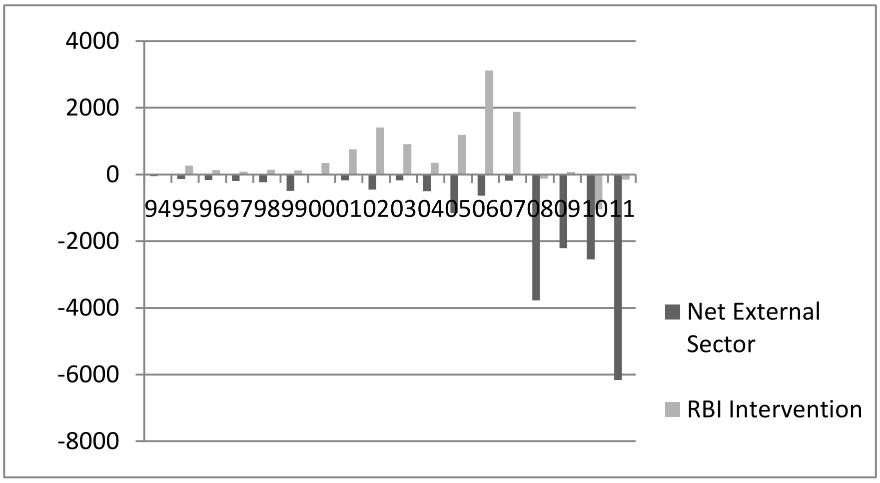

Figure 4: Net External Sector and RBI Intervention for the period 1994 - 2012

With detailed empirical analysis, the paper attempts to fulfill following objectives: 1. To examine the randomness in money velocities and if it satisfies a random walk hypothesis since it has been seen that the fluctuations in money velocity exhibits random walk behavior for some developed and industrial countries especially after 1982. The answer to this question would further enable us choose suitable model for understanding the dynamics of money velocity. 2. To find if there are structural breaks and change points in the annual velocities and then finding a suitable model to predict the velocities taking care of change points. 3. To check if the amount of growth of electronic transactions in the country during last decade are sufficient to have an influence on money velocity. 4. Last and important part of the study includes the analysis of how do external sectors like – trade balance, foreign debt inflow, foreign investments, remittances from abroad, and the interventions from Reserve Bank of India put an impact on

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money velocity. The idea is to come up with quantitative model for the case if at all external sector has an impact on money velocity.

2. Literature Review

The attempts to study money velocity of India was started by Iyer (1970), where a declining trend was observed in velocity of both narrow as well as broad money [3] during the period 1955 through 1969. This study was followed by Saravane (1971) where a sectorial approach in analyzing money demand as well as velocity of money was presented [4] and it was pointed out that the velocity of money for the household sector ranges between 5.44 and 6.91 during 1950-51 to 1962-63 with marginal year to year fluctuations. Kamaiah and Paul (1979) attempted to fit a velocity function for India using annual data up to the year 1974-75 based on the conventional variables, such as, real income, interest rates and price expectations [5]. Unsatisfactory empirical results, however, led them to conclude that, 'velocity, being a ratio, could behave in a complex way that few specified determinants might not explain fully its movements'. Accordingly they suggested that velocity behavior should be modeled using time-series methods rather than econometric model. Subsequently, Kamiah, Paul et al. (1987) used Autoregressive Integrated Moving Average (ARIMA) method on quarterly data for the period 1970-71 to 1981-82 to reveal that velocity behavior of narrow money does not appear to follow the random walk hypothesis [6].

Some important findings regarding the analysis of the predictability of velocity, the Bordo and Jonung study (1987) finds itself in a bind as it turns out that in all the five countries examined (i.e. US, UK, Canada, Sweden, and Norway), velocity behavior exhibits a random walk [7]. This phenomenon implies that past changes in velocity alone cannot be used to predict future changes. One of the pioneer researches in this area was carried out Narendra Jadhav in 1994. He talked about different factors affecting the velocity of money in case of India. He estimated the velocity function using seasonally adjusted quarterly velocity series for broad money (V3) covering the period 1970-II to1988-I. He considered the explanatory variables like the real income, the spread of banking, interest rates, and the degree of financial sophistication achieved in the economy [8]. With these variables he has done the regression analysis and found that these factors explain 90 percent variation in the velocity of broad money in the Indian economy.

A study by Karemera, Harper and Oguledo (1998) on random walk behavior of monetary velocity in G-7 countries (Britain, Canada, France, Germany, Japan, Italy and the United States) [9] suggests that most of the monetary velocities of the countries do not obey random walk hypothesis except for US M1 and M2 velocities. Pedro (2005) establishes that money velocity in US [10] is pro-cyclical and discusses the implications of this behavior on monetary policy in an endogenous framework. Mendizabal (2006) analyses the long run behavior of money velocities with an emphasis on the impact of inflation on money velocity. The results in his paper provide an [11] explanation for low correlation between money velocity and inflation for a sample of 79 countries. Omer (2010) investigated the stability of money velocity for Pakistan and showed that [12] interest rate fluctuations are independent of their money velocities. A recent study in Indian case by Sitikantha and Subhadhra (2011) brings out that conventional determinants of velocity are statistically significant for Indian data [13], however they suggest that estimated parameters may not be adequate for further assessment of velocity.

3. Data and Methods

The data on M1 and M3 measures covering the period 1981-82 to 2012-13 and M2 and M4 measures covering the period 1994-95 to 2012-2013 on income and nominal GDP data at factor cost (current prices) are taken from the Handbook of Statistics on the Indian Economy (2012), Reserve Bank of India, Mumbai. For i= 1,2,3,4 the notations qV_i and $qmvel$ represent quarterly money velocities whereas V_i and $emvel$ denote yearly velocities.

To test the randomness in data series, runs test has been used. In the test we have used our null hypothesis is that that the data is random. There is only one parameter h as output of our program. The value h=1 rejects the null hypothesis at the 5% significance level, and if h = 0 then we fail to reject null hypothesis. The augmented Dickey–Fuller test (ADF) is a test for a unit root in a time series sample. The testing procedure for the ADF test is the same as for the Dickey–Fuller test. The null hypothesis of the Augmented Dickey-Fuller t-test is that the time series has a unit root that is non-stationary. In case if we find the time series is non-stationary, we can make it stationary by differencing of suitable order. The decision whether a series is stationary or non-stationary is determined by the p value obtained.

Finding change points are essential to understand structural breaks in the time series which must be taken care of before we forecast the series. There are number of methods available to find change points, however our analysis is based on PELT algorithm. This is a new approach to search for change points, which is exact and under mild conditions has a computational cost that is linear in the number of data points: the Pruned Exact Linear Time (PELT) method. This approach is based on the algorithm of Jackson et al. (2005), but involves a pruning step within the dynamic program. This pruning reduces the computational cost of the method, but does not affect the exactness of the resulting segmentation [14]. It can be applied to find change points under a range of statistical criteria such as penalized likelihood [15], quasi-likelihood (Braun et al., 2000) and cumulative sum of squares [16] (Inclan and Tiao, 1994).

Granger Causality tests have been used for determining whether one time series is useful in forecasting another. The test is performed on two stationary time series $x_t \; and \; y_t$ with the null hypothesis that y_t does not Granger cause x_t. The program that has been used in the analysis gives two parameters (F, c_v) where F is the value of the F-statistic and c_v the critical value from the F-distribution. For our analysis if $F > c_v$ then we reject the null hypothesis that y_t doesn't Granger cause x_t .

Auto-Regressive Integrated Moving Average (ARIMA) model has been used for modeling stationary time series. A non-seasonal ARIMA model is classified as an "ARIMA (p, d, q)" model, where p is the number of autoregressive terms, d is the number of non-seasonal differences order of differencing required to make the series stationary q is the number of lagged forecast errors in the prediction equation. ARIMA (p, d, q) define models with an Auto-Regressive part of order p, a Moving average part of order q and having applied d order differencing can be written as

$$\left(1-\varphi_1 B-\varphi_2 B^2-\cdots-\varphi_p B^p\right)(1-B)^d y_t=c+\left(1-\mu_1 B-\mu_1 B^2-\cdots-\mu_q B^q\right)\epsilon_t$$

where, μ_i , φ_i, are constant, B is the backshift operator and $c = \mu(1-\varphi_1-\varphi_2 \ldots \varphi_p)$ and μ is the mean of $(1-B)^d y_t$. Some well-known special cases arise naturally. For example, an ARIMA (0, 1, 0) model (or I(1) model) is given by $X_t = X_{t-1} + \epsilon_t$ which is simply a random walk.

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If the time series is stationary, or if it has been transformed into a stationary time series by differencing d times, the next step is to select the appropriate ARIMA model, which means finding the values of most appropriate values of p and q for an ARIMA (p, d, q) model, which is done by examining the correlogram and partial correlogram of the stationary time series. If the correlogram is zero after lag n, and the partial correlogram tails off to zero after lag m, then p=m and q =n may be chosen. However, the value of p, d and q is chosen in accordance to principle of parsimony states that the model with the fewest parameters is best.

Linear interdependencies among multiple time series are captured in a vector autoregressive framework (VAR). Let $Y_t = (y_{1t}, y_{2t}, \ldots, y_{nt})$ denote an (n×1) vector of time series variables. The basic p-lag vector autoregressive ($VAR(p)$) model has the form

$$Y_t = c + \pi_1 Y_{t-1} + \pi_2 Y_{t-2} + \cdots + \pi_p Y_{t-p} + \epsilon_t, t = 1, \ldots, t$$

$where\ \Pi_i$ are $(n \times n)$ coefficient matrices and ε_t is an (n×1). All the variables in the model have of the same order of integration. The order p of VAR model has been determined by Akaike information criterion (AIC) and Bayesian Information Criterion (BIC) values.

4. Empirical Results and Discussions

4.1. Randomness in Behavior of Money Velocity fluctuations

Let $\{X_k\}$ be a sequence of independent, identically distributed discrete random variables such that for each positive integer n, we let $S_n = X_1 + X_2 + \cdots + X_n$. The sequence $\{S_n\}$ is called a random walk. Random walk follows Markov Property i.e future states of the process (conditional on both past and present values) depends only upon the present state, not on the sequence of events that preceded it. Fig 5 gives a visualization of the particle positions in a two dimensional random walk.

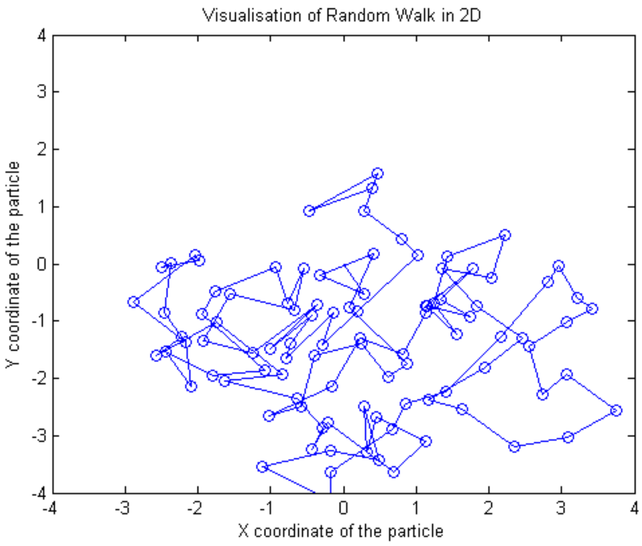

Figure 5. Illustration of a 2D Random Walk

The random walk hypothesis is a financial theory which states that stock market prices evolve according to a random walk and thus cannot be predicted. In this article, as mentioned in the objectives, the empirical tests are performed to answer if the Indian money velocities show randomness in behavior and follow random walk hypothesis. To figure out the randomness in the Indian data two kinds of velocities viz. yearly and quarterly from the given data are calculated:

Yearly Velocities: V_1, V_3: 1981-2012, V_2, V_4 : 1994 - 2012

Quarterly Velocities: V_1, qV_2, qV_3, qV_4 : 2004 - 2012

On the above data, Runs Test was performed. There is only one parameter h as output of our program. If h = 1 if it rejects the null hypothesis at the 5% significance level, and if h = 0 then null hypothesis is failed to be rejected. The results are summarized in the Fig 6.

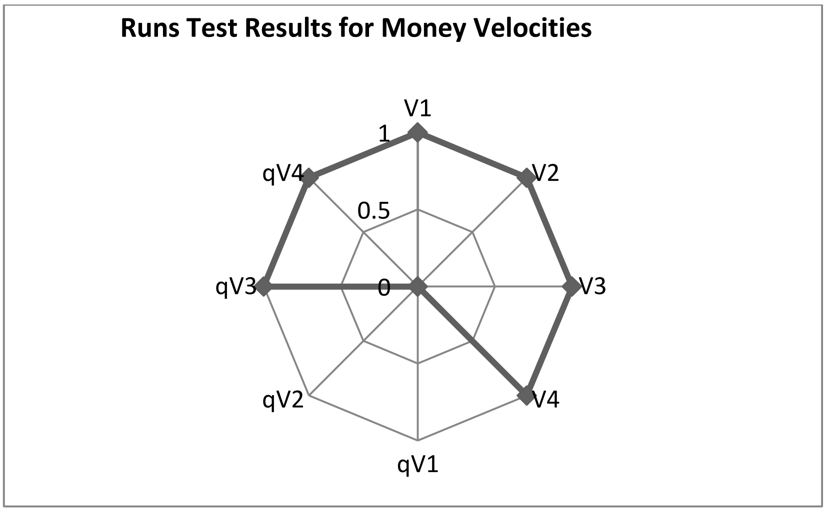

Figure 6: Runs Test Results

In the plot in Figure 4, the radial values represent the value of h. It is evident that except qV_1 and qV_2, all the velocities have the value of h=1, which rejects the null and hence the velocities are not random. So, except for qV_1 and qV_2, none of the velocities would follow random walk hypothesis. Now, whether qV_1 and qV_2 follows the hypothesis is answered later.

4.2. Modeling Money Velocities

The time series for the money velocities have been modeled using Auto Regressive Integrated Moving Average Model (ARIMA). However, before using ARIMA, stationarity of data series and check for structural breaks or change points needs to be done which has been done using PELT algorithm. From the analysis of the plots in Fig. 7, we see that there are change points in the time series of yearly money velocities except for V_4. The change points are primarily located around the year 2000. Although the sudden changes in the money and GDP have led to these change points, yet the precise reasons for the change points is difficult to be ascertained since both of them comprise of a number of sub components and changes have occurred in multiple components.

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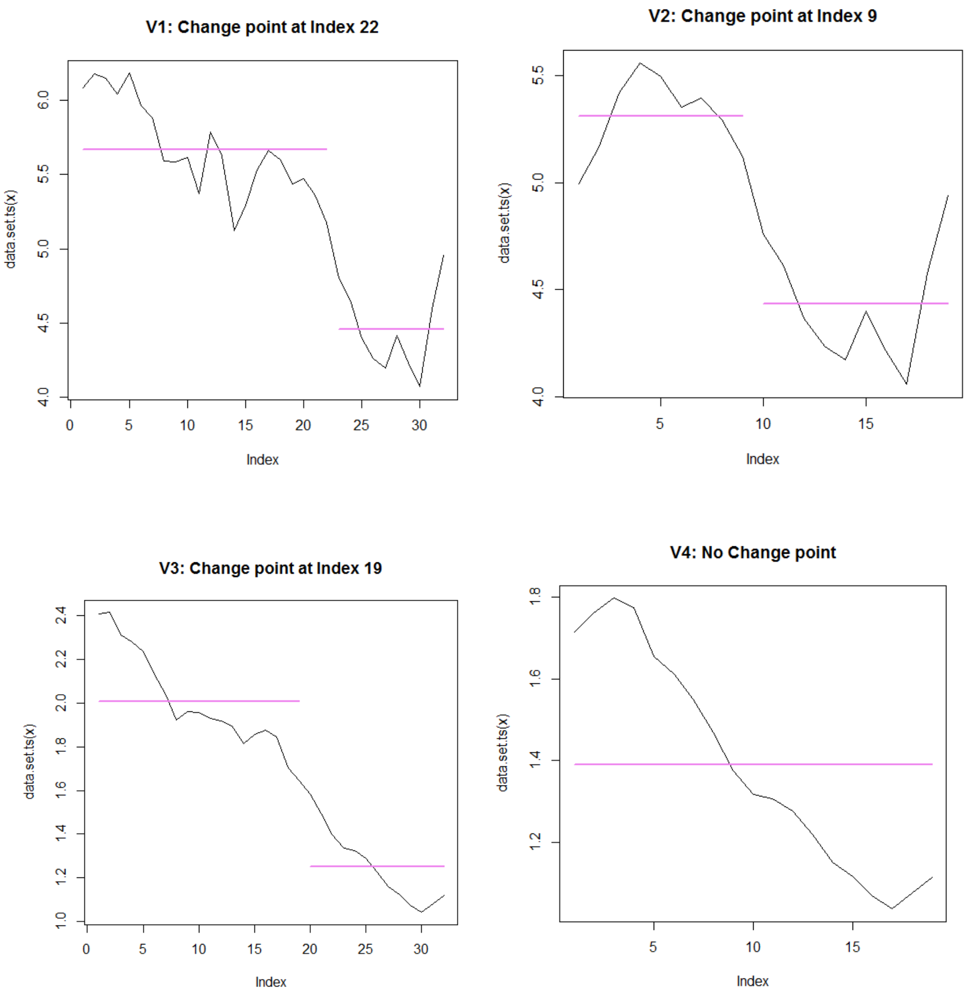


Figure 7: Change point detection in yearly money velocities

Table 1. Results of ADF tests on money velocities

Non Stationary Series	Stationary Series
1. All yearly velocity series and up to second order difference of (V_1,V_2,V_3) after change points. 2. All quarterly velocities and up to first order difference of qV_1, qV_2, qV_3) after change points.	1. All quarterly velocities qV_1, qV_2, qV_3, qV_4 at their second order difference. Note that there were no change points in quarterly velocities. 2. Second order difference of yearly V_4.

The analysis so far leads to a conclusion that quarterly money velocities (2004-2012) have no change points and are stationary after second order difference. So, ARIMA model is fit on qV_1, qV_2, qV_3, qV_4 on the second differenced data points of each of velocities. This means among the three parameters (p, d, q) we have d = 2. To get the values of p and q, the Auto-correlation functions (ACF) and partial autocorrelation functions (PACF) of the velocities are investigated. If ACF goes below significant bounds after m lags and PACF goes below significant bounds after n lags, we choose ARMA (n, 0) or ARMA (0, m) whichever has minimum parameters. In case PACF's doesn't falls down very rapidly we would choose ARMA (p, q). From Fig. 8 we see that PACF falls off to zero after lag3 while ACF falls off to zero after 16 for both the quarterly money velocities qV1 and qV2. So ARMA (3, 0) is chosen. Further

PACFs falls off to zero very rapidly hence a mixed model won't be appropriate. Since d = 2, so the best ARIMA that fits here is ARIMA (3, 2, 0).

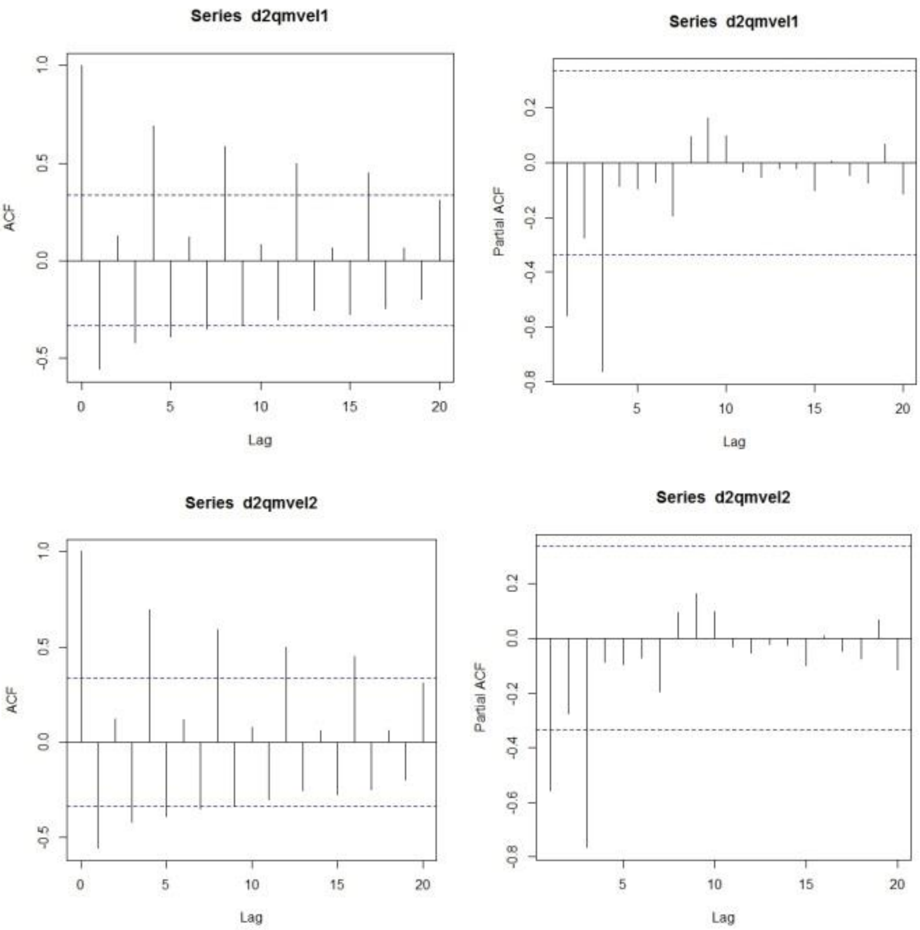
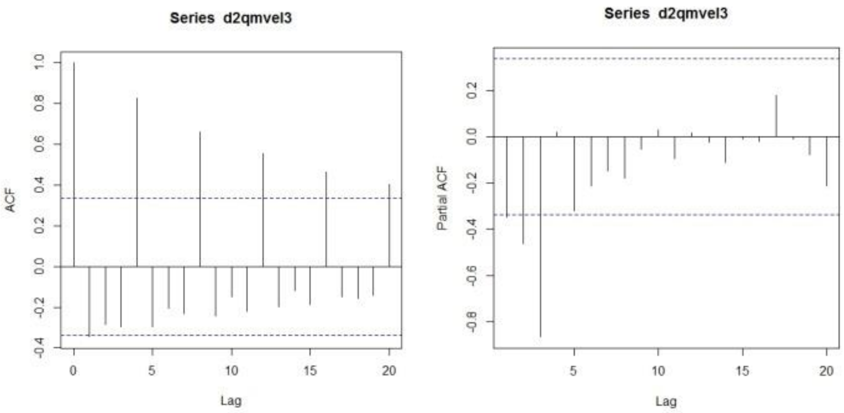


Figure 8 a. ACFs and PACFs for second difference qV_1 and qV_2



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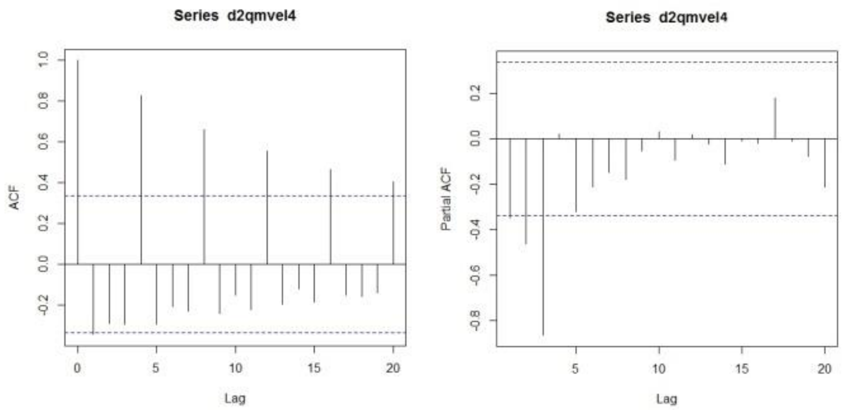


Figure 8 b. ACFs and PACFs for second difference qV_1 and qV_2

From the discussions in section of research methodologies, it is known that ARIMA (0, 1, 0) is nothing but a random walk and we have seen that qV1 and qV2 shows randomness in their behavior. But the conclusion from ARIMA model says ARIMA (3, 2, 0) is the best fit for all quarterly velocities. Hence we conclude that even qV1 and qV2 also don't follow random walk hypothesis. The following Table 2 gives the estimated coefficients with standard errors for each money velocities. The ACF of residuals have been analyzed and it is found that the autocorrelations are close to zero which is also confirmed by Box Tests (is a type of statistical test of whether any of a group of autocorrelations of a time series are different from zero with null hypothesis as the data are independently distributed). The p Values of Box tests suggest that the residuals are indeed a white noise. Substituting the values of p = 3, d = 2 and q = 0 in the following equation we get,

$$\left(1-\varphi_1 B-\varphi_2 B^2-\cdots-\varphi_p B^p\right)(1-B)^d y_t = c+\left(1-\mu_1 B-\mu_1 B^2-\cdots-\mu_q B^q\right)\epsilon_t$$

$$(1-\varphi_1 B-\varphi_2 B^2-\varphi_3 B^3)(1-B)^2 y_t = c+\epsilon_t$$

$where\ B^p y_t = y_{t-p}\ and\ c = \mu(1-\varphi_1-\varphi_2-\varphi_3)\ and\ \mu\ is\ the\ mean\ of\ \ (1-B)^2 y_t$
The estimated coefficients of $\varphi_1, \varphi_2, \varphi_3$ from ARIMA (3, 2, 0) mentioned in Table 2.

Table 2. Estimated coefficients of ARIMA (3, 2, 0) model for different money velocities

Money Velocities	$\boldsymbol{\varphi_1}$	**SE in** $\boldsymbol{\varphi_1}$	$\boldsymbol{\varphi_2}$	**SE in** $\boldsymbol{\varphi_2}$	$\boldsymbol{\varphi_3}$	**SE in** $\boldsymbol{\varphi_3}$
$\boldsymbol{qV_1}$	-0.960	0.086	-0.891	0.104	-0.859	0.077
$\boldsymbol{qV_2}$	-0.959	0.086	-0.891	0.1042	-0.859	0.077
$\boldsymbol{qV_3}$	-0.914	0.064	-0.921	0.060	-0.904	0.054
$\boldsymbol{qV_4}$	-0.914	0.060	-0.921	0.064	-0.905	0.054

From Table 2, the estimated coefficients have very low standard deviation and standard error as evident from the table which leaves a positive remark on the validity of the model.

Instead of deriving equations explicitly for each money velocities in terms of the estimated coefficients, we have directly used "ARIMA forecast" in R which essentially uses the above coefficients. The next 6 predicted values are mentioned in Table 3 for each velocity with their standard errors. Further, out of sample forecast also gives a low error (ranging from 8 -15%). Figure 9 represents fan chart plots for the forecast. The area in the shaded region contains the forecasted curve for the values mentioned in Table 3.

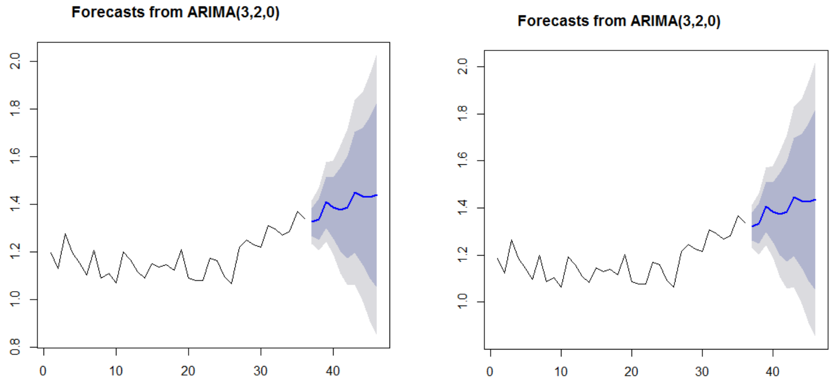


Figure 9a. Fan charts for predicted money velocities (left: qV_1 and right: qV_2)

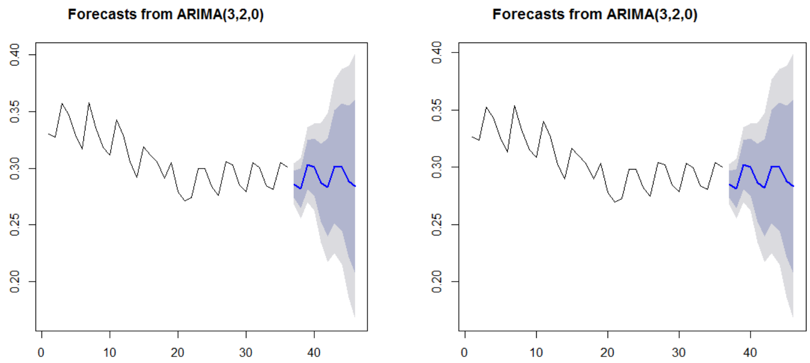


Figure 9a. Fan charts for predicted money velocities (left: qV_3 and right :qV_4)

The predicted values are for next 6 quarters beginning from October 2013 to March 2015. An important point to note here is that usually ARIMA is used for short term forecasts. Once the standard errors are seen to be increasing, remodeling needs to be done.

Table 3: Forecasted Values of next 6 quarterly money velocities using ARIMA (3, 2, 0)

Time Period October 2013 to March 2015	Predicted qV_1	Standard Error in Predicted qV_1	Predicted qV_2	Standard Error in Predicted qV_2
Q1	1.409	0.0845	1.405	0.0839
Q2	1.386	0.1000	1.382	0.0992
Q3	1.377	0.1370	1.373	0.1358
Q4	1.388	0.1678	1.384	0.1665
Q5	1.449	0.1968	1.445	0.1952
Q6	1.432	0.2236	1.428	0.2218

Time Period October 2013 to March 2015	Predicted qV_3	Standard Error in Predicted qV_3	Predicted qV_4	Standard Error in Predicted qV_4
Q1	0.3030	0.0168	0.3022	0.0166
Q2	0.3010	0.0196	0.3002	0.0194
Q3	0.2872	0.0269	0.2864	0.0267
Q4	0.2829	0.0335	0.2821	0.0331
Q5	0.3015	0.0390	0.3007	0.0386
Q6	0.3011	0.0439	0.3004	0.0435

4.3. Is the volume of electronic transactions sufficient to influence money velocities in India?

The question has been answered using Granger Causality test. The time series used for this purpose are qV_1, qV_2, qV_3, qV_4 and quarterly value of total electronic transactions. The null hypothesis that y_t does not Granger-cause x_t is failed to be rejected if and only if no lagged values of y_t are retained in the regression. Following research methodologies section, the program uses two parameters (F, c_v) where F is the value of the F-statistic and c_v the critical value from the F-distribution. In this analysis if $F > c_v$ then the null hypothesis is rejected concluding that that y_t doesn't Granger cause x_t . Table 4 gives the results of the tests.

Table 4. Granger Causality tests for electronic transactions and money velocity.

X_t	Y_t	F	C_v	Results
qV_1	e-transaction	0.79	4.19	Y_t *does not Granger cause* X_t
qV_2	e-transaction	0.48	4.17	Y_t *does not Granger cause* X_t
qV_3	e-transaction	0.41	4.17	Y_t *does not Granger cause* X_t
qV_4	e-transaction	0.40	418	Y_t *does not Granger cause* X_t

From Table 4, we easily conclude that electronic transactions in India are not causing money velocity. However from intuitive arguments, one might infer that electronic transactions should be influencing money velocity. There are few studies available in this area to compare our results with. The interpretation of this could be that the volume of electronic transactions going on in India is insufficient to cause changes in money velocity which is actually dependent on number of other factors affecting money supply and GDP.

4.4. External Sectors and Money Velocity

To analyze if the impact of external sector on money velocity, once again Granger causality tests are performed to ensure that money velocity is influenced by external sector or not. We do the same thing for RBI intervention. In this analysis the data of yearly money velocity, yearly net external sector amount and RBI interventions (in Rupees Billions) for the duration of 1994 - 2012. The net external sector consisted of trade balance, total foreign investment (portfolio and direct), debt inflow and the external assistance. Using Augmented Dickey Fuller tests, it was observed that the variables used here are stationary at their second order of difference and hence the causality tests are performed on second order differenced time series. The results were positive here suggesting both net external sectors and RBI interventions do Granger cause money velocities. The results are summarized in Table 5.

Table 5: Granger Causality tests for External sector, RBI interventions and money velocity.

X_t	Y_t	F	C_v	Results
Yearly money velocity 1	Net external sector	6.42	4.65	Y_t $Granger\ cause\ X_t$
Yearly money velocity 2	Net external sector	6.40	4.66	Y_t $Granger\ cause\ X_t$
Yearly money velocity 3	Net external sector	11.81	3.80	Y_t $Granger\ cause\ X_t$
Yearly money velocity 4	Net external sector	11.22	3.88	Y_t $Granger\ cause\ X_t$
Yearly money velocity 1	RBI interventions	16.03	4.74	Y_t $Granger\ cause\ X_t$
Yearly money velocity 2	RBI interventions	15.95	4.73	Y_t $Granger\ cause\ X_t$
Yearly money velocity 3	RBI interventions	7.57	3.98	Y_t $Granger\ cause\ X_t$
Yearly money velocity 4	RBI interventions	7.09	3.98	Y_t $Granger\ cause\ X_t$

External Sectors and Money Velocity in a VAR framework

From the results of Granger Causality tests in the previous section, it can be observed that both RBI interventions and net external sector have an influence on the money velocity. The final part is to find the inter-relationship between the variables and predict the future values. Vector Auto-Regressive Framework (VAR) has been used to analyze these relationships. The time series has been taken after the change points. However we observe using ADF tests that after the year of change points the RBI intervention data is non-stationary till fourth order differences. So, if we take all other series at fourth order difference, this reduces the number of data points and applying VAR on the RBI interventions and money velocities we observe that we have large errors the estimated VAR coefficients and also in predictions. This is in one way good for the Indian economy because if RBI interventions are predictable then this might lead to expectations in the market and there might be an exploitation of policy of intervening to stabilize the exchange rate. So we present here the analysis of external sector and money velocities in VAR model only. The order of VAR was chosen using AIC (Akaike Information Criterion) value and BIC (Bayesian Information Criterion) values. VAR (1) had lowest both AIC and BIC values. The values for VAR (2) were close but for higher order VAR, singularities were produced in the computation of the projection matrix. So VAR (1) is chosen as the best model.

The estimated coefficients of VAR (1) obtained for different money velocities together with the fit, ACF and PACF plots of the residuals and standard errors have been tabulated below.

$Estimation\ results\ for\ equation\ d2emvel1$ (Second order difference yearly money velocity time series):

$$(d2mvel1)_t = l1.(d2emvel1)_{t-1} + l2.(d2extsec2)_{t-1} + const + trend$$

Table 6. Results of VAR (1) model for money velocity 1 and External Sector.

Coefficients	Estimate	Standard Error	t-value	Pr(>|t|)
$l1$	-0.5669	0.2782	-2.038	0.111
$l2$	8.961×10^{-5}	0.3250	2.757	0.051
$const$	-7.474×10^{-2}	0.2068	-0.361	0.736
$trend$	3.690×10^{-2}	0.0356	1.036	0.359

Residual Standard Error: 0.2244 with 4 degrees of freedom	
Multiple R-Squared: 0.729,	Adjusted R-squared: 0.5257

$Estimation\ results\ for\ equation\ d2extsec2$: (Second order difference yearly external sector time series)

$$(d2extsec2)_t = l1.(d2emvel1)_{t-1} + l2.(d2extsec2)_{t-1} + const + trend$$

Coefficients	Estimate	Standard Error	t-value	Pr(>|t|)
$l1$	-6849.95	2130.76	-3.215	0.0324
$l2$	-0.405	0.2089	-1.627	0.1791
$const$	-387.00	1584.31	0.244	0.8190
$trend$	-20.26	272.84	-0.074	0.9444

Residual Standard Error: 0.1919 with 4 degrees of freedom	
Multiple R-Squared: 0.792,	Adjusted R-squared: 0.6375

The blue line in the fit depicts the fit of VAR model where as black lines are the data points of second order differenced series. The impulse response functions for orthogonal responses are also plotted for future predictions. We have presented here the detailed results of velocity 1 and velocity 3 only since the results for velocity 2 and 4 very closely resemble velocity 1 and velocity 3 respectively.

Table 6. AIC and BIC values for lag 1 and lag 2.

For velocities 1 and 2			For velocities 3 and 4		
Lags	AIC	BIC	Lags	AIC	BIC
[1,]	12.14	12.09	[1,]	6.73	6.68
[2,]	12.58	12.50	[2,]	7.68	7.60

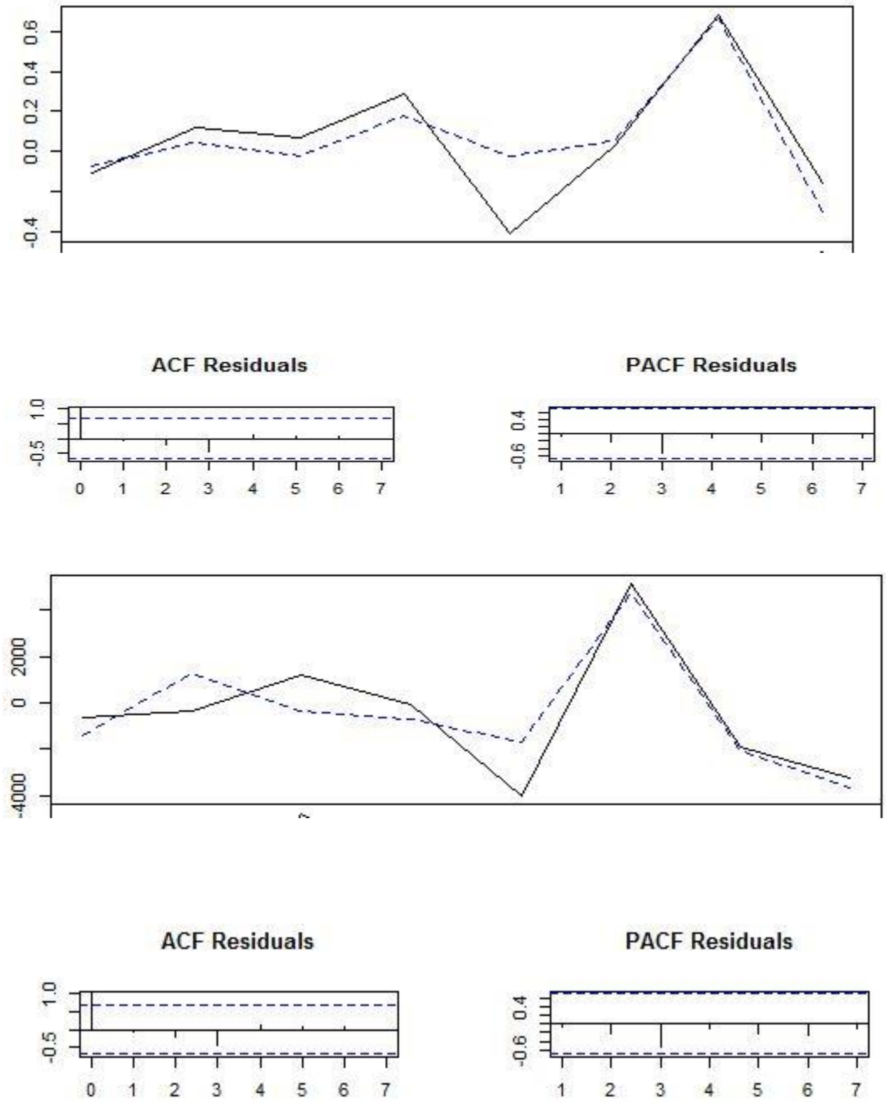


Figure 12. Fit and ACF, PACF for Residuals Plots for equations from VAR (1) model. Top two plots: For equation for money velocity (d2emvel1) in terms of other variables. Bottom two plots: For equation for external sector (d2extsec1) in terms of other variable.

$Estimation\ results\ for\ equation\ d2emvel3$:
$(d2emvel3)_t = l1.(d2emvel3)_{t-1} + l2.(d2extsec2)_{t-1} + const + trend$

Table 6. Results of VAR (1) model for money velocity 3 and External Sector.

Coefficients	Estimate	Standard Error	t-value	Pr(>|t|)
$l1$	-0.3365	0.2069	-1.626	0.1792
$l2$	7.526×10^{-6}	2.671×10^{-6}	2.818	0.0479
$const$	-4.374×10^{-2}	1.738×10^{-2}	-2.517	0.656
$trend$	9.865×10^{-3}	-3.055×10^{-3}	3.229	0.0320

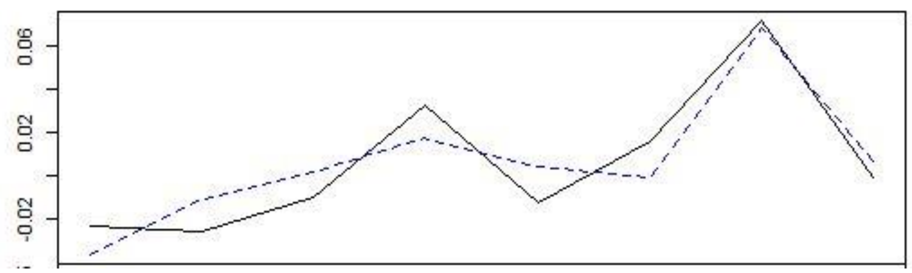
Residual Standard Error: 0.0184 with 4 degrees of freedom	
Multiple R-Squared: 0.818,	Adjusted R-squared: 0.682

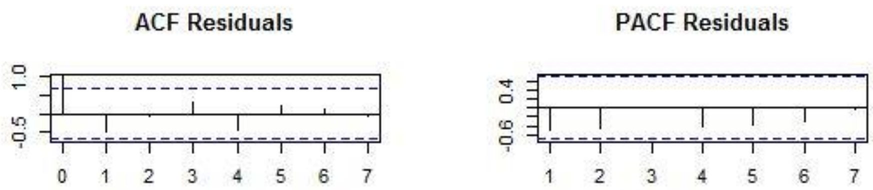
$Estimation\ results\ for\ equation\ d2extsec2$:

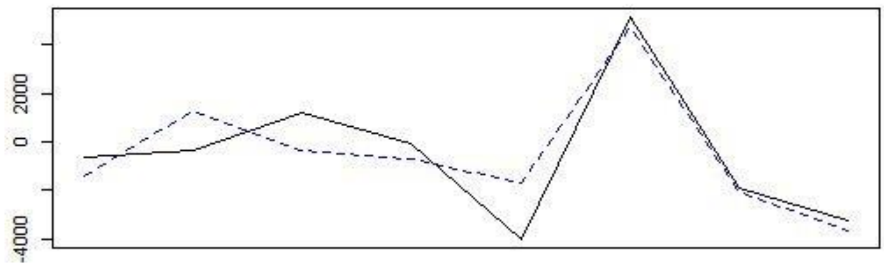
$$(d2extsec2)_t = l1.\,(d2emvel3)_{t-1} + l2.\,(d2extsec2)_{t-1} + const + trend$$

Coefficients	Estimate	Standard Error	t-value	Pr(>|t|)
$l1$	-4.945×10^4	2.65×10^4	-1.866	0.135
$l2$	-0.474	0.3421	-1.1386	0.238
$const$	-15.54	0.226	-0.007	0.995
$trend$	-26.58	3.91×10^2	0.068	0.949

Residual Standard Error: 0.2379 with 4 degrees of freedom	
Multiple R-Squared: 0.603,	Adjusted R-squared: 0.3055







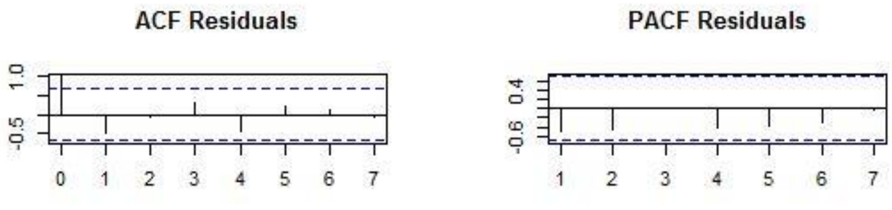


Figure 13. Fit and ACF, PACF for Residuals Plots for equations from VAR (1) model. Top two plots: For equation for money velocity (d2emvel3) in terms of other variables. Bottom two plots: For equation for external sector (d2extsec3) in terms of other variables.

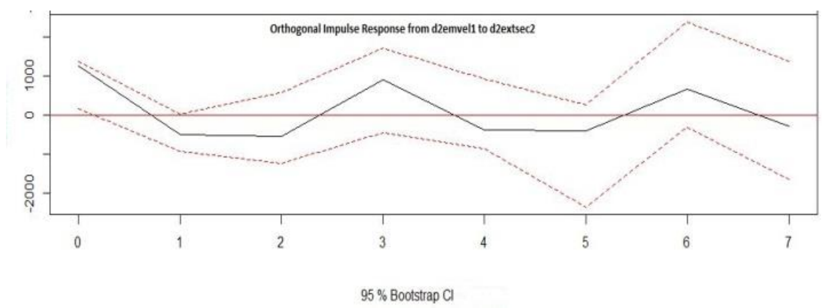


Figure 14. Impulse Response Function of money velocity 1 to external sector.

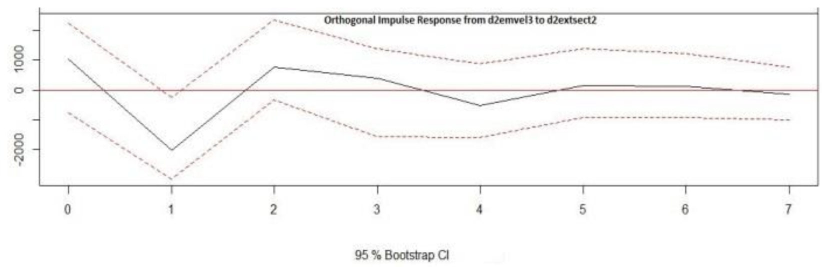


Figure 15. Impulse Response Function of money velocity 3 to external sector.

So far we concluded that VAR (1) the appropriate choice of model to analyze the interrelationship between yearly money velocity and external sector. An important point to keep in mind here is we have used stationary time series for analysis which is actually the second order difference of original time series. The notations d2emvel1, d2emvel3 and d2extsec2 refer to second order difference series of money velocity 1, money velocity 3 and external sector respectively. From the fit plot of VAR (1) in Fig. 12 and Fig 13 we indeed observe that VAR (1) for yearly money velocities 1 and 3 in terms of lag 1 of respective velocities and external sector seems to be a good fit. This is also supported by autocorrelation functions and partial auto-correlation functions, since it is evident that there are no autocorrelations at any lag in the ACF and PACF plot of residuals. From the values of R^2 and adjusted R^2 so obtained it can be seen that there is good measure of agreement between observed and modeled values and where the modeled values. But our primary goal is to analyze the impact of external sector on the money velocity, so we focus on the equations obtained for money velocities in terms of lag 1 of other variables.

When the t values and the corresponding probabilities of the estimated coefficients are compared, it can be observed that the coefficients of money velocity (d2emvel1 and d2emvel3) are statistically more significant than that of coefficients of external sector (d2extsect2) implying that although external sector affect the money velocity, however this is not the sole factor affecting it. The equations obtained from VAR (1) for money velocities are mentioned below.

$$\Delta^2(emvel1)_t = -0.07474 + (-0.569)\Delta^2(emvel)_{t-1} + (8.961 * 10^{-5})\Delta^2(\mathrm{extsec})_{t-1} + \varepsilon_t$$

$$\Delta^2(emvel3)_t = -0.0.043 + (-0.3365)\Delta^2(emvel)_{t-1} + (7.526 * 10^{-6})\Delta^2(\mathrm{extsec})_{t-1} + \varepsilon_t$$

Note that the above equations can easily be reduced to the equation in terms of the original time series just by substituting,

$$\begin{aligned} \Delta^2 X_t &= \Delta X_t - \Delta X_{t-1} \\ &= X_t - 2X_{t-1} + X_{t-2} \end{aligned}$$

The stationarity and stability of the model have been confirmed from the eigenvalues of matrix A in the equation $y_t = Ay_{t-1} + \epsilon_t$. Matrix can be obtained from VAR (1) equations.

For money velocity 1,

$$A = [-0.57, -6849.9574;\ 8.961 \times 10^{-5}, -0.4050] \quad with\ eigenvalues\ -0.49\ \pm 0.78i$$

For money velocity 3,

$$A = [-0.3365, -4.945 \times 10^4; 7.526 * 10^{-6}, -4.742 \times 10^{-1}] \quad with\ eigenvalues\ 0.4 \pm\ 0.6i$$

In each case it is observed that the matrix A is non-singular and modulus of eigenvalues are less than 1 and hence the system is stable and stationary.

Impulse Responses Money Velocities for VAR (1): Impulse response functions represent the response of a variable to a unit impulse in another variable occurring some time period ago. We have analyzed the orthogonal (so that the components of ϵ_t are uncorrelated) impulse response of money using Cholesky decomposition on VAR model to one standard deviation shock to the external sector. For velocity 1 we observe that it has a negative response for two years then it becomes positive. The same thing is seen to repeat for a few more forecasts. However the same is not true for velocity 3. It shows a positive response for most of the years which a small negative response after every 3-4 years. But there is negligible response after 10 years for a unit shock given at time t.

5. Discussions and Conclusions

Our quest started with the search for randomness in Indian money velocities and if it follows a random walk hypothesis. From runs test we concluded that except quarterly velocities 1 and 2 all other velocities are non - random. Later on, ARIMA confirmed that even those two velocities do not exhibit random walk behavior. This result is consistent to the findings by Karemera, Harper and Oguledo (1998), which states [8] that that monetary velocity of G7 countries (Britain, Canada, France, Germany, Japan, Italy and the United States) did not obey random walk hypothesis except for the US M1 and M2 velocity. But we also observed that the findings of Bordo and Jonung study (1987) suggest that for all five countries viz. US, UK, Canada, Sweden, and Norway, the velocity behavior exhibits a random walk. Furthermore, as mentioned in [8], random walk behavior of money velocity may reflect the fluctuations of income component of the velocity which consequently affect money velocity. So, to conclude why the money velocity in a particular country obeys random walk behavior requires deeper analysis, which leaves a scope of a future research. The key advantage of analyzing random walk behavior is that we are able to choose a suitable time series model to analyze the further dynamics of the money velocity in India else we would have gone for stochastic modelling.

In the next part with an objective to understand the dynamics of money velocity in India, we observed that ARIMA (3, 2, 0) is an appropriate model to visualize the dynamics and predict the future values. However, from the fan charts (Fig. 9) of predicted velocities we observe that we cannot make long term predictions as true for ARIMA models in general. The predicted values of 6 quarters have also been given. To make better predictions after those values we need to revisit the velocities with new data points and check for suitable ARIMA again.

Furthermore, we have tried to establish if the amount of electronic transactions going on in the country is sufficient to cause money velocity and Granger Causality tests proved that the money velocity is yet to be affected by electronic transactions in the country. However we observed both the external sectors and RBI interventions have an impact on the money velocities and are Granger caused by the two factors. Then we tried to analyze the interrelationship between the variables in a VAR framework but we found that due to non stationarity of RBI intervention data after the change points, VAR model is inappropriate here. So we continued with the VAR model on external sectors and money velocities. The suitable model was found be VAR with order 1. This model was seen to be good fitting, having very low autocorrelations values for residuals, stationary and stable. At the end we tried to forecast and analyze the implications and responses of money velocities via impulse response functions where we observed that yearly money velocity has more positive responses to the impulse from external sector than velocity 1 while velocity 1 was found to show some repetitive responses in near future predictions.

The importance of monetary theory and policy lies in the relationship between money, output and prices and the crux of this relationship is money velocity. Monetary authorities do not have a direct control over velocity of money, however if the underlying factors responsible for fluctuations in velocity and its behavior are discovered, it would be a lot more convenient for policy makers to come up with a stable monetary policy.

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References

Annual Report, Reserve Bank of India 2009.

Bordo M D and Jonung L (1987), 'The Long-run Behavior of the Velocity of Circulation', Cambridge University Press, New York.

Braun, J. V., Braun, R. K., and Muller, H. G (2000). (Multiple change point fitting via quasi likelihood, with application to DNA sequence segmentation. Biometrika, 87(2):301-314,.

Inclan, C. and Tiao (1994.), G. C. Use of cumulative sums of squares for retrospective detection of changes of variance. JASA, 89(427):913-923.

Froyen, Richard T (1990.). *Macroeconomics: Theories and Policies*. 3rd Edition. Macmillan Publishing Company: New York. p. 70-71.

Money Stock Measures, Reserve Bank of India
Retrieved from: http://www.rbi.org.in/scripts/BS_ViewBulletin.aspx?Id=14487

Iyer K. S. R. (1970), 'Income Velocity of Monetary Resources: Past Trends and Projections', Economic and Political Weekly, September 19th.

Saravane M (1971), The Demand for Money in India: a Sectoral approach, Vikas Publications, Delhi,

Jackson, B., Sargle, J. D., Barnes, D., Arabhi, S., Alt, A., Gioumousis, P., Gwin, E., Sangtrakulcharoen, P., Tan, L., and Tsai, T. T. (2005). An algorithm for optimal partitioning of data on an interval. IEEE, Signal Processing Letters, 12(2):105-108.

Jadhav N. (1994), ‘Monetary Economics for India’, Macmillan India Limited, Delhi, ch. 3 pp.-81 -100.

Kamaiah B and Paul M. T. (1987)., 'Velocity of Money in India: A Time Series Analysis', Working Paper, NIBM.

Kamaiah B. and Paul M. T. (1979.), “An Empirical Study of Velocity of Money Functions in India: 1951-52 to 1974-75”, Vishleshan, Vol. 5, No. 4. December.

Karemera D., Harper V., Oguledo I.V.(1998), ‘Random walks and monetary velocity in the G7 countries: a new evidence from multiple variance ratio tests’ Applied Economics, Volume 30, pp 569-578.

Leao P. (2005), ‘Why does velocity of money move pro-cyclically?’, International Review of Applied Economics, Volume 19, No. 1, pp. 119-135.

Mendizabal H.R., (2006), ‘The Behavior of Money Velocity in High and Low Inflation Countries’, Journal of Money, Credit and Banking, Vol. 38, No. 1, pp. 209-228

Omer M. (2010), ‘Velocity of Money Functions in Pakistan and Lessons for Monetary Policy’, SBP Research Bulletin, Volume 6, Number 2, pp 37-55.

Pattanaik S., Subhadra S., (2011), The Velocity Crowding-Out Impact: Why High Money Growth is Not Always Inflationary, Reserve Bank of India Working Paper No. 6.