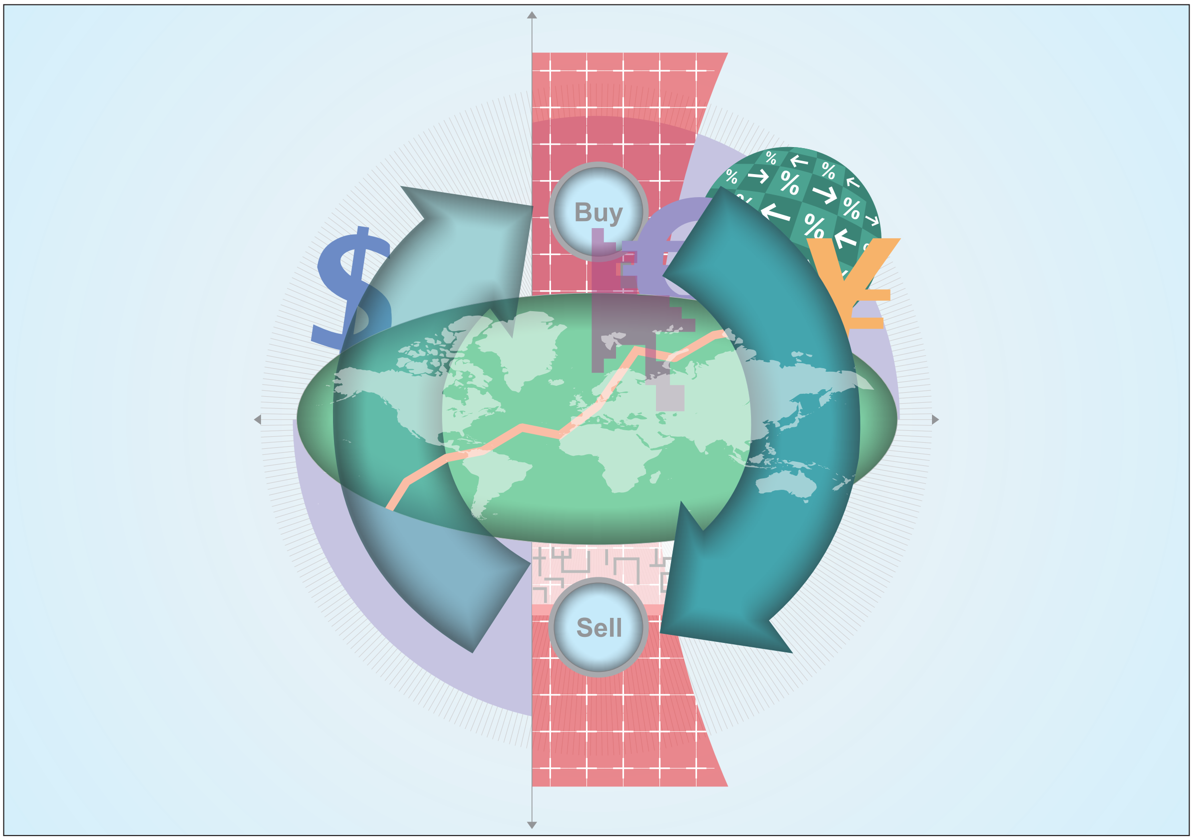

The International Journal of Applied Economics & Finance

ISSN 1991-0886

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The International Journal of Applied Economics and Finance 5 (2): 97-113, 2011
ISSN 1991-0886 / DOI: 10.3923/ijaef.2011.97.113

Volatility Regimes and Calendar Anomaly in Foreign Exchange Market

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ABSTRACT

Well-documented financial market, particularly stock market anomalies question the efficiency of financial market and hence hint towards inadequacy of the underlying model. Literature on foreign exchange market anomalies, either apparent or real, however, has not been so extensive. Due to its large trading activities, the foreign exchange market is often taken to be a liquid and efficient one. The issue of foreign exchange market efficiency is important as the prices of foreign assets, goods and factors of production depend largely on the changes in exchange rates. This paper, while addressing this issue explores the possible presence of calendar anomaly, specifically the day-of-the-week effect in the Indian Rupee-US Dollar exchange rate volatility over a period of January 1998 to April 2010. The emphasis on foreign exchange volatility stems from its huge impact on real economy, other financial markets, capital gain or losses from exchange rate changes and government intervention. With its aim to look for the presence of calendar anomaly to assess the impact of daily transaction mechanism on volatility, the study further explores the changing nature of calendar anomaly over the different volatility regimes. Such exploration will check whether calendar anomaly is a mere statistical aberration and time specific phenomenon. Using the ICSS test, the study finds five volatility regimes and strong presence of day-of-the week effect could be documented during the phases of high volatility. However, the Monday and Tuesday effects remained in all but one volatility regimes.

Key words: Exchange rate, volatility break, efficient market hypothesis, day-of-the week effect, structural change

INTRODUCTION

Financial market anomalies are well-documented in literature and have drawn attention of researchers as a deviation from the traditional theories of asset pricing. The presence of such anomaly signals towards arbitrage opportunities and hence questions the efficiency of financial market. Following (Fama, 1970) any lack of market efficiency might be an indication of the inadequacy of the underlying model. Stock market returns over the years have been characterized by significant anomalies such as month-of-the year effect (Rozeff and Kinney, 1976; Bhardwaj and Brooks, 1992; Eleswarapu and Reinganum, 1993; Gultekin and Gultekin, 1983; Chang and Pinegar, 1986; Maxwell, 1998; Bhabra *et al.*, 1999; Lazar *et al.*, 2006; Agathee, 2008; Chakrabarti and Sen, 2007, 2010; Sarkar *et al.*, 2008; Lim *et al.*, 2010) day-of-the week effect

(French, 1980; Kamara, 1997; Agrawal and Tandon, 1994; Brooks and Persand, 2001; Bayar and Kanb, 2002; Apolinario *et al.*, 2006; Basher and Sadorsky, 2006; Sutheebanjard and Premchaiswadi, 2010), turn-of-the month and holiday effect (Lakonishok and Smidt, 1988; Ariel, 1987; Cadsby and Ratner, 1992; Ziemba, 1991; Hensel and Ziemba, 1996; Kunkel and Compton, 1998; Brockman and Michayluk, 1998), size effect (Banz, 1981; Sehgal, 2005; Wong *et al.*, 2006; Rutledge *et al.*, 2008; Zhou and Zhang, 2009; Zhiwu and Jindra, 2009) and announcement effect (Ball and Brown, 1968; Fama *et al.*, 1969; McConnell and Muscarella, 1985; Klein, 1986; Jensen and Ruback, 1983). Some anomalies are often related to idiosyncratic behavior of investors in the market (La Porta *et al.*, 1998, Gao, 2009; Hammami and Abaoub, 2010). However, such a huge literature is often termed as over-discovery of anomalies (Schwert, 1989). Observed anomalies are often questioned on the ground that these might be mere statistical aberration and might result from a sample selection bias. These criticisms appear legitimate as some of these anomalies tend to disappear or reverse with re-specification of the underlying model or through trading strategies adopted by investors.

While stock markets are subject to anomalies, either apparent or real, literature on foreign exchange market anomalies has not been so extensive. Foreign exchange market has been the most active financial market. Due to its large trading activities, the market is often taken to be a liquid and efficient one (Froot and Thaler, 1990). The issue of foreign exchange market efficiency is significant as the prices of foreign assets, goods and factors of production are influenced if not determined by the change in exchange rates. This paper, while addressing this issue will not emphasize on the relationship between exchange rate and macroeconomic variables. Rather it will seek to explore the possible presence of calendar anomaly, specifically the day-of-the-week effect in the foreign exchange market volatility.

The issue of foreign exchange market volatility, with its massive impact on real economy, international trade, other financial markets and government intervention needs to be seriously addressed. It is the volatility that ultimately determines the gains or losses through changing exchange rates. Presence of calendar anomaly is likely to reflect the impact of daily transaction mechanism on volatility. The present study looks for the possible presence of calendar anomaly in the Indian Rupee-US Dollar exchange rate over a period of January 1998 to April 2010. Moreover it seeks to relate the nature of calendar anomaly to the different phases of exchange rate volatility. Such exploration is important as it will portray the changing profit opportunities with switching of volatility regimes. Further, it is likely to remove the sample selection bias and will check whether calendar anomaly is a temporary and time specific phenomenon.

MATERIALS AND METHODS

Daily exchange rate between Indian Rupee and US Dollar over a period of January 1998 to April 2010 is available on seven-day basis. The analysis is based on the change in exchange rates (that is appreciation and depreciation) computed as $\ln(e_t/e_{t-1})$ where e_t and e_{t-1} are exchange rates in period t and t-1 respectively.

The study will be conducted in two phases. First, it will look for the volatility breaks and the consequent volatility regimes in the Rupee-USD exchange rate series. Shifts in mean although is widely discussed in a number of studies is left out as it lies outside the scope of this work. In the second stage, possible presence of day-of-the-week effect in volatility will be explored in each of these volatility regimes separately and the results will be compared.

Detection of structural break: Structural breaks or structural changes refer to persistent and pronounced macroeconomic shifts in the data generating process. Longer the period under consideration, higher is the probability of observing structural breaks. Let us consider a simple AR (1) process:

$$y_t = \alpha + \rho y_{t-1} + \varepsilon_t \tag{1}$$

$$E\varepsilon_t^2 = \sigma^2 \tag{2}$$

where, ε_t is a time series of serially uncorrelated shocks. If the series is stationary, the parameters α, ρ and σ^2 are constant over time. A structural break is said to be occurred if at least one of the parameters changes permanently at some point (Hansen, 2001). The date the parameter changes value is known as the breakdate. According to Brooks (2002), structural breaks are irreversible in nature. The reasons behind occurrence of structural breaks are manifold. Economic policies, for example change in exchange rate regime, change in interest rate, monetary policy shifts or trade policies may cause structural breaks to occur. There may also be some unidentifiable reasons that cause breaks in return or volatility (Valentinyi-Endresz, 2004).

Identification of multiple structural breaks in variance: The ICSS test: The Iterative Cumulative Sum of Squares or simply the ICSS algorithm by Inclan and Tiao (1994) is used to detect sudden changes in unconditional variance for a stochastic process. It is used to detect multiple shifts in volatility. The algorithm is based on the premise that the time series displays a stationary variance over an initial period which is changed due to a shock to the system and again continues to be stationary till it experiences another shock in the future. This process is repeated over time till all the breakpoints are identified.

The original model by Inclan and Tiao: Breaks in unconditional variance: Let $C_k = \sum_{t=1}^{k} a_t^2$, $k = 1, \ldots, T$ for a series of independent observations with $\{a_t\}$, $a_t \sim iidN(0, \sigma^2)$ and $t = 1,2,\ldots,T$ and σ^2 is the unconditional variance:

$$\sigma^2 = \begin{cases} \tau_0, & 1 < t < k_1 \\ \tau_1, & k_1 < t < k_2 \\ & \ldots\ldots \\ \tau_{N_T}, & k_{N_T} < t < T \end{cases} \tag{3}$$

where, $1 < k_1 < k_2 < \ldots < k_{N_T} < T$ are the points where the breaks in variances occur, i.e., the breakpoints. And N_T is the total number of such changes for T observations. Within each interval, the variance is $\tau_j^2, \quad j = 0,1,\ldots\ldots N_T$

And let the centralized or normalized cumulative sum of squares be D_K.

D_K is defined as:

$$D_k = \frac{C_k}{C_T} - \frac{K}{T} \quad D_0 = D_T = 0 \tag{4}$$

where, C_T is the sum of squared residuals for the whole sample period.

If the variance doesn't change within the sample period, i.e. with no volatility shift, D_k will oscillate around zero, i.e., if D_k is plotted against k, it will be a straight line. It will drift upward or downward when there is a change in the variance and it will exhibit a pattern going out of some specified boundaries (provided by a critical value based on the distribution of D_k) with high probability. If at some k, say k*, the maximum absolute value of D_k, given by:

$$\text{Max}_k \left| \sqrt{T/2D_k} \right|$$

exceeds the critical value, the null hypothesis of constant variance is rejected and k* will be regarded as an estimate of the change point. Under variance homogeneity, $\sqrt{T/2D_k}$ behaves like a Brownian bridge asymptotically.

For multiple breakpoints however, the usefulness of the D_k function is questionable due to masking effect. To avoid this, Inclan and Tiao (1994) designed an iterative algorithm that uses successive application of the D_k function at different points in the time series to look for possible shift in volatility.

Modified ICSS test: Breaks in conditional variance: Sanso *et al.* (2003) found significant size distortions for the ICSS test when the process is non-mesokurtic and conditional heteroscedasticity is present. This leads to spurious results for the unconditional variance hence making the original ICSS test of little use in financial time series which is often characterized by fat tails and conditional heteroscedasticity. To correct this, they incorporated two new tests that explicitly consider the fourth moment properties of the disturbances and the conditional heteroscedasticity.

The first test, also known as the k_1 test makes the asymptotic distribution free of nuisance parameters for iid zero mean random variables:

$$k_1 = \sup_K |T^{-1/2} B_k|, \quad k = 1, \ldots\ldots, T \tag{5}$$

where:

$$B_k = \frac{C_k - \frac{k}{T} C_T}{\sqrt{\hat{\eta}_4 - \hat{\sigma}^4}}$$

while:

$$\hat{\eta}_4 = T^{-1} \sum_{t=1}^{T} \varepsilon_t^4$$

and

$$\hat{\sigma}^4 = T^{-1} C_T$$

This statistic is free of any nuisance parameter.

And the second test, the k_2 test is able to address the issues of fat tails and persistent volatility:

$$k_2 = \sup_k | T^{-\frac{1}{2}} G_k | \tag{6}$$

where:

$$G_k = \hat{\omega}_4^{-\frac{1}{2}} \left(C_k - \frac{k}{T} C_T \right)$$

$\hat{\omega}_4$ is a consistent estimator of ω_4. A nonparametric estimator of ω_4 can be expressed as:

$$\hat{\omega}_4 = \frac{1}{T}\sum_{i=1}^{T}(\varepsilon_t^2 - \hat{\sigma}^2)^2 + \frac{2}{T}\sum_{l=1}^{m}\omega(l,m)\sum_{t=1}^{T}(\varepsilon_t^2 - \hat{\sigma}^2)(\varepsilon_{t-1}^2 - \hat{\sigma}^2) \tag{7}$$

where, $\omega(l,m)$ is a lag window, such as Bartlett and defined as $\omega(l,m) = [1-l/(m+1)]$.

The bandwidth m is chosen using (Newey and West, 1994) technique. As it incorporates the fat tail and conditional variance, the k_2 test is more powerful than the original Inclan-Tiao test or even the k_1 test. Kokoszka and Leipus (2000) proposed a similar test but they assume an ARCH (∞) type model. But the k_2 test employs a more general framework and hence a better suited model for our purpose.

In reality, there is little difference between structural breaks and regime switch. Although in principal there is some theoretical difference between the two, in practice, the difference is often indistinct. Structural breaks can efficiently capture regime switches (Altissimo and Corradi, 2003; Gonzalo and Pitarakis, 2002; Valentinyi-Endresz, 2004). The modified ICSS test is used to identify breaks in conditional volatility, i.e., the point where the conditional volatility jumps from one stationary level to another one. This is the same premise as presented in Markov regime switching models, where the system moves from a high (low) volatility regime to a low (high) volatility regime.

Presence of day-of-the-week-effect: Generalized Autoregressive Conditional Heteroscedasticity or GARCH models are better suited to detect presence of calendar anomaly in financial time series due to their ability to capture properties of financial time series such as time-varying volatility of higher order moments, autocorrelated returns, volatility persistence, fat tails and non-normality (Siddiqui, 2009; Al-Khazali *et al.*, 2008). The study uses a proper-ordered GARCH (p,q) model where daily dummies are incorporated in the variance equation only. Since the data are available on seven-day basis, there will be six dummies, treating Sunday as the reference day. This is quite different from the existing literature as most of the earlier studies considered a five-day week. The relevant model has a mean equation and a variance equation given as:

Mean equation:

$$Y_t = C + X_t^I \beta + \varepsilon_t \tag{8}$$

Variance equation:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-1}^2 + \sum_{j=1}^{p} \beta_j \sigma_{j-1}^2 + \sum_{k=1}^{6} C_k D_k \tag{9}$$

where, p is the order of autoregressive GARCH terms and *q* is the order of moving average ARCH terms. The six D_k's are the day dummy variables. The restrictions on the model are, p = 0, q>0, ω>0, $\alpha_i \geq 0$, I = 1,...,q and $\beta_j \geq 0$, j = 1,./...,p. The best model is chosen on the basis of minimum Schwartz (Bayesian) Information Criterion (Schwarz, 1978) and Hannan-Quinn Criterion or HQC (Hannan and Quinn, 1979). For large samples (sample size >500) HQC performs best whereas SIC suits smaller samples (sample size <500). This is based on the findings by Shittu and Asemota (2009).

The coefficients c_k's will give the coefficient difference between the k'th dummy variable and the reference day. Hence, the coefficient for k'th dummy variable will be $\hat{w} + \hat{c}$. A significant $\hat{w} + \hat{c}$ for k'th dummy variable will imply significance of k'th day-dummy variable. The significance will be tested by the Wald test of coefficient restrictions. The Wald statistic measures how close the unrestricted estimates $\hat{w} + \hat{c}$ come to satisfying the restrictions under the null hypothesis. If the restrictions are in fact true, then the unrestricted estimates should come close to satisfying the restrictions. Under the null hypothesis H_0 the Wald statistic has an asymptotic X^2 (q) distribution, where q is the number of restrictions under H_0.

To check whether the variance equation is properly specified, the ARCH-LM test will be carried out. If the variance equation is correctly specified, there should be no ARCH left in the standardized residuals (Engle, 1982). This test was initially motivated by the observation that in many financial time series, the magnitude of residuals appeared to be related to the magnitude of recent residuals. The ARCH LM test statistic is computed from an auxiliary test regression. To test the null hypothesis that there is no ARCH up to order q in the residuals, (10) will be run:

$$e^2_t = \beta_0 + \beta_1 e^2_{t-1} + \beta_2 e^2_{t-2} + \ldots\ldots\ldots\ldots + \beta_q e^2_{t-q} + v_t \tag{10}$$

where, e is the residual. This is a regression of the squared residuals on constant and lagged squared residuals up to order q. An F-statistic is reported which is an omitted variable test for the joint significance of all lagged squared residuals. The Engle's LM test statistic is computed as the number of observations times the R^2 from the test regression. The exact finite sample distribution of the F-statistic under H_0 is not known but the LM test statistic is asymptotically distributed as $X^2(q)$ under quite general conditions.

RESULTS

Structural breaks in volatility of Indian rupee-US dollar exchange rate: Using the modified ICSS test, the break dates in the Indian Rupee-US Dollar exchange rate were identified (Table 1). Results from only k_2 test were considered because of its ability to model conditional volatility and volatility persistence.

The Rs/US Dollar exchange rate had four breaks in volatility. With the identification of break dates, five sub-periods or volatility regimes were constructed. The nature of volatility had been different over these five volatility regimes. A look at Fig. 1 could make the proposition clear.

The first two regimes were of moderate volatility. The second regime had been longest extending over a period of almost six years. Volatility had remained at a low level over this period. Volatility tended to be sharper in the third regime. The last two regimes were characterized by significantly high volatility. Volatility had been sharper in the fourth regime. Now the study was extended to explore the presence and nature of day-of-the-week effect in the foreign exchange market in these volatility regimes.

Day-of-the-week effect in Indian rupee-US dollar exchange rate: The inquiry started from the analysis of descriptive statistics in the five regimes. The exchange rate return series had been negatively skewed in the first, fourth and fifth regime while it had been positively skewed in the remaining two. Value of kurtosis had remained over three in all the five regimes. Significant Jarque-Berra test statistic suggested non-normality of the return series in all the five regimes. The series had been tested for the possible presence of unit root using the Augmented Dickey Fuller and Phillips-Perron test statistic. The null hypothesis of unit root had been rejected in all the five regimes. The exchange-rate return series with fat tail, excessive kurtosis and non-normality could hence be best modeled using a suitable GARCH model Table 2.

Results for applying GARCH model in regime 1: On the basis of the selection criterion, an ARMA (1,1)-GARCH(1,1) model with Generalized Error Distribution was found to be suitable for regime 1. The residuals up to 36 lags showed presence of no autocorrelation and ARCH-LM test showed absence of any remaining ARCH effect in residual. In the variance equation, there had

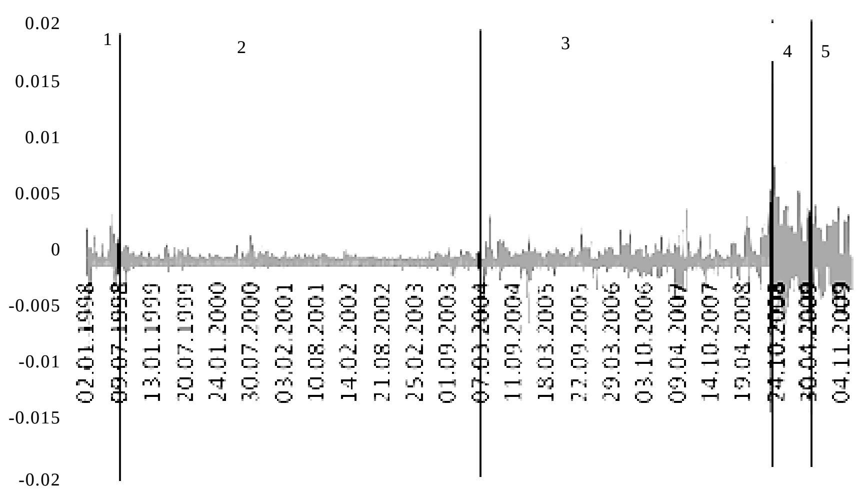

Fig. 1: Volatility regimes in Indian rupee-US Dollar exchange rate

Table 1: Break dates for the Indian rupee-US dollar exchange rate return series

Break dates	Volatility regimes	Dates
24/08/98	Regime 1	January 1, 1998 to August 24, 1998
22/03/04	Regime 2	August 25, 1998 to March 22, 2004
8/9/2008	Regime 3	March 23, 2004 to September 8, 2008
19/05/09	Regime 4	September 9, 2008 to May 19, 2009
	Regime 5	May 20, 2009 to April 30, 2010

Table 2: Regime-wise descriptive statistics for Indian rupee-US dollar exchange rate

Statistical values	Regime 1	Regime 2	Regime 3	Regime 4	Regime 5
Mean	0.00014	0.00001	-0.000003	0.00014	-0.00011
Std. Dev.	0.002	0.0001	0.001	0.004	0.002
Skewness	-1.816	1.006	0.044	-0.117	-0.022
Kurtosis	16.960	19.165	7.923	5.211	3.939
Jarque-Bera	2028.71*	22532.52*	1647.37*	52.13*	12.74*
ADF test statistic	-13.85*	-47.77*	-38.34*	-14.65*	-6.63*
PP test statistic	-13.82*	-47.95*	-38.73*	-14.57*	-22.09*

*Denotes significance at 1% level

Table 3: Day-of-the-week effect in volatility regime 1

Included observations: 234 after adjustments

Convergence achieved after 28 iterations

Presample variance: backcast (parameter = 0.7)

GARCH = C(4)+C(5)*RESID(-1)^2+C(6)*GARCH(-1)+C(7)*MON+C(8) *TUE+C(9)*WED+C(10)*THURS+C(11)*FRI+C(12)*SAT

Analysis	Coefficient	SE	Z-statistic	Prob.
Mean equatiou				
C	4.49E-06	2.44E-05	0.183996	0.854
AR(1)	-0.00905	0.859107	-0.01054	0.9916
MA(1)	-0.0101	0.857199	-0.01179	0.9906
Variance equatiou				
C	-2.01E-07	1.43E-07	-1.4048	0.1601
RESID(-1)^2	0.15348	0.040326	3.805968	0.0001
GARCH(-1)	5.46E-01	8.21E-02	6.648198	0.00
MON	2.10E-06	5.68E-07	3.697115	0.00
TUE	4.08E-08	5.09E-07	0.080184	0.94
WED	5.18E-07	4.79E-07	1.082805	0.28
THURS	6.80E-07	3.67E-07	1.849735	0.06
FRI	7.29E-07	4.91E-07	1.483065	0.14
SAT	1.02E-08	4.50E-07	0.022707	0.98
GED PARAMETER	8.68E-01	7.06E-02	12.29877	0
Wald test				
H_0: C(4)+C(7) = 0	H_0 rejected at 1% level			
H_0: C(4)+C(8) = 0	H_0 accepted at 1% level			
H_0: C(4)+C(9) = 0	H_0 accepted at 1% level			
H_0: C(4)+C(10) = 0	H_0 accepted at 1% level			
H_0: C(4)+C(11) = 0	H_0 accepted at 1% level			
H_0: C(4)+C(12) = 0	H_0 accepted at 1% level			
Heteroskedasticity Test: ARCH				
F-statistic 0.21 Prob. F (36,161) = 1				
Obs*R-squared 8.98 Prob. Chi-Square (36) = 1				

been no Sunday effect. On the basis of Wald test only a significantly negative Monday effect was found to exist (Table 3) in volatility.

Results for applying GARCH model in regime 2: An ARMA (1,1)-GARCH(3,3) model with Generalized Error Distribution was found suitable for regime 2. There had been neither serial auto correlation nor remaining ARCH effects in the residuals up to 36 lags. Over this period of low volatility, only a positive Tuesday effect was found to exist (Table 4) in volatility.

Table 4: Day-of-the-week effect in volatility regime 2

Included observations: 2037

Convergence achieved after 22 iterations

Presample variance: backcast (parameter = 0.7)

GARCH = C(4)+C(5)*RESID(-1)^2+C(6)*RESID(-2)^2+C(7)*RESID(-3)^2+C(8)*GARCH(-1)+C(9)*GARCH(-2)+C(10)*GARCH(-3)+C(11)*MON+C(12)*TUE+C(13)*WED+C(14)*THURS+C(15)*FRI+ C(16)*SAT

Analysis	Coefficient	SE	Z-statistic	Prob.
Mean equatiou				
C	-4.94E-07	3.74E-06	-0.13228	0.8948
AR(1)	-0.05667	0.171734	-0.33001	0.7414
MA(1)	-0.05883	0.169204	-0.3477	0.7281
Variance equatiou				
C	-4.71E-08	1.43E-07	-0.32906	0.7421
RESID(-1)^2	1.39E-01	1.49E-02	9.288097	0
RESID(-2)^2	4.79E-02	3.88E-01	0.123467	0.9017
RESID(-3)^2	1.27E-02	1.03E-01	0.122982	0.9021
GARCH(-1)	4.01E-01	2.80E+00	0.143329	0.886
GARCH(-2)	3.43E-02	1.45E+00	0.023657	0.9811
GARCH(-3)	3.52E-02	1.95E-01	0.180768	0.8565
MON	3.89E-08	2.96E-07	0.131293	0.8955
TUE	2.59E-07	1.61E-07	1.605972	0.1083
WED	5.78E-08	4.62E-07	0.125249	0.9003
THURS	9.95E-08	1.85E-07	0.538635	5.90E-01
FRI	9.81E-08	3.31E-08	2.959246	0.0031
SAT	1.06E-07	1.49E-08	7.091191	0
GED parameter	1.522085	0.024867	61.20833	0
Wald test				
H_0: C(4)+C(11) = 0	H_0 accepted at 1% level			
H_0: C(4)+C(12) = 0	H_0 rejected at 1% level			
H_0: C(4)+C(13) = 0	H_0 accepted at 1% level			
H_0: C(4)+C(14) = 0	H_0 accepted at 1% level			
H_0: C(4)+C(15) = 0	H_0 accepted at 1% level			
H_0: C(4)+C(16) = 0	H_0 accepted at 1% level			
Heteroskedasticity test: ARCH				
F-statistic	0.696323	Prob. F(36,2006)	0.79	
Obs*R-squared	10.47362	Prob. Chi-Square(36)	0.78	

Results for applying GARCH model in regime 3: On the basis of selection criterion, ARMA(3,3)-GARCH(3,1) with Generalized Error Distribution was selected. Residuals were characterized by no serial correlation and no remaining ARCH effect. Over this period of moderate but increasing volatility, significant Monday, Tuesday, Thursday and Saturday effects were found to exist in volatility. Of these effects, only Monday effect had been negative (Table 5).

Results for applying GARCH model in regime 4: ARMA (1,1)-GARCH(1,1) with student's t distribution in error was selected for regime 4. The residuals showed absence of serial auto correlation or additional ARCH effects. Over this period of sharp volatility, a negative Monday effect along with positive Sunday, Tuesday and Saturday effects were found to exist in volatility (Table 6).

Table 5: Day-of-the-week effect in volatility regime 3

Included observations: 1631

Convergence achieved after 68 iterations

Presample variance: backcast (parameter = 0.7)

GARCH = C(8)+C(9)*RESID(-1)^2+C(10)*RESID(-2)^2+C(11)*RESID(-3)^2+C(12)*GARCH(-1)+C(13)*MON+C(14)*TUE+C(15)*WED+C(16)*THURS+C(17)*FRI+C(18)*SAT

Analysis	Coefficient	SE	z-Statistic	Prob.
Mean equatiou				
C	1.13E-07	1.85E-05	0.006136	0.9951
AR(1)	-0.00385	6.788957	-0.00057	0.9995
AR(2)	-0.00639	5.715531	-0.00112	0.9991
AR(3)	0.007193	3.485701	0.002064	0.9984
MA(1)	0.002736	6.788707	0.000403	0.9997
MA(2)	0.006494	5.715276	0.001136	0.9991
MA(3)	-0.00996	3.486962	-0.00286	0.9977
Variance equatiou				
C	-5.99E-	1.54E-07	-0.38995	0.6966
RESID(-1)^2	0.13543	0.020631	6.564419	0
RESID(-2)^2	-0.05731	0.02297	-2.49495	0.0126
RESID(-3)^2	0.0115	0.002746	4.1884	0
GARCH(-1)	0.411031	0.153635	2.675368	0.0075
MON	-4.69E-	1.10E-07	-0.42585	0.6702
TUE	2.09E-06	2.40E-07	8.709754	0
WED	7.74E-08	2.22E-07	0.349227	0.7269
THURS	1.12E-06	1.38E-07	8.115236	0
FRI	2.96E-07	1.29E-07	2.297239	0.0216
SAT	6.56E-07	1.37E-07	4.775215	0
GED parameter	1.394093	0.034918	39.92462	0
Wald test				
H_0: C(8)+C(13) = 0	H_0 rejected at 1% level			
H_0: C(8)+C(14) = 0	H_0 rejected at 1% level			
H_0: C(8)+C(15) = 0	H_0 accepted at 1% level			
H_0: C(8)+C(16) = 0	H_0 rejected at 1% level			
H_0: C(8)+C(17) = 0	H_0 accepted at 1% level			
H_0: C(8)+C(18) = 0	H_0 rejected at 1% level			
Heteroskedasticity test: ARCH				
F-statistic	0.96	Prob. F(36,1558)	0.53	
Obs*R-squared	34.96	Prob. Chi-Square(36)	0.53	

Results for applying GARCH model in regime 5: ARMA (1,1)-GARCH (1,1) with normal error distribution had been suitable for regime 5. Over this period of high volatility, all the day-of-the-week effects had been significantly positive in volatility (Table 7). There had been no serial auto correlation or remaining ARCH effects in residual.

Thus, over the periods of high volatility, the number of the day-of-the week effect had been much more compared to that in the low volatility periods. However, day-of-the week effect had changed significantly over the different volatility phases. The Monday effect had remained in all but the second volatility regime and the Tuesday effect had been insignificant only in the first regime.

Table 6: Day-of-the-week effect in volatility regime 4

Included observations: 253

Convergence achieved after 7 iterations

Presample variance: backcast (parameter = 0.7)

GARCH = C(4)+C(5)*RESID(-1)^2+C(6)*GARCH(-1)+C(7)*MON+C(8)*TUE+C(9)*WED+C(10)*THURS+C(11)*FRI+C(12)*SAT

Analysis	Coefficient	Std. Error	z-Statistic	Prob.
Mean Equatiou				
C	1.53E-05	0.000209	0.073204	0.9416
AR(1)	0.037757	0.949494	0.039765	0.9683
MA(1)	0.038574	0.9563	0.040337	0.9678
Variance Equatiou				
C	1.63E-05	5.11E-06	3.198271	0.0014
RESID(-1)^2	0.166745	0.036053	4.625054	0
GARCH(-1)	0.626345	0.047131	13.28953	0
MON	-2.97E-05	8.14E-06	-3.64682	0.0003
TUE	-7.16E-06	5.67E-06	-1.26211	0.2069
WED	-1.15E-05	5.98E-06	-1.92561	0.0542
THURS	-1.58E-05	5.98E-06	-2.63877	0.0083
FRI	-1.65E-05	5.85E-06	-2.82071	0.0048
SAT	-1.35E-05	6.03E-06	-2.23449	0.0255
T-DIST. DOF	19.99936	9.777968	2.045349	0.0408
Wald Test				
H_0: C(4)+C(7) = 0	H_0 rejected at 1% level			
H_0: C(4)+C(8) = 0	H_0 rejected at 1% level			
H_0: C(4)+C(9) = 0	H_0 accepted at 1% level			
H_0: C(4)+C(10) = 0	H_0 accepted at 1% level			
H_0: C(4)+C(11) = 0	H_0 accepted at 1% level			
H_0: C(4)+C(12) = 0	H_0 rejected at 1% level			
Heteroskedasticity Test: ARCH				
F-statistic	0.71	Prob. F(36,180)	0.88	
Obs*R-squared	27.14	Prob. Chi-Square(36)	0.86	

Table 7: Day-of-the-week effect in volatility regime 5

Included observations: 346

Convergence achieved after 25 iterations

Presample variance: backcast (parameter = 0.7)

GARCH = C(4)+C(5)*RESID(-1)^2+C(6)*GARCH(-1)+C(7)*MON+C(8) *TUE+C(9)*WED+C(10)*THURS+C(11)*FRI+C(12)*SAT

Analysis	Coefficient	Std. Error	z-Statistic	Prob.
Mean equatiou				
C	-0.00017	5.35E-05	-3.18243	0.0015
AR(1)	0.489662	0.089006	5.501439	0
A(1)	-0.66148	0.068537	-9.65149	0
Variance equatiou				
C	1.24E-05	3.64E-06	3.418615	0.0006
RESID(-1)^2	0.300649	0.051819	5.80194	0
GARCH(-1)	-0.19944	0.069494	-2.86985	0.0041
MON	-9.36E-06	3.00E-06	-3.12366	0.0018
TUE	-6.53E-06	3.89E-06	-1.68052	0.0929
WED	-9.49E-06	3.73E-06	-2.54423	0.011
THURS	-9.30E-06	3.68E-06	-2.52456	0.0116
FRI	-1.06E-05	3.64E-06	-2.92006	0.0035
SAT	-9.83E-06	3.66E-06	-2.68805	0.0072

Table 7: Continue

Wald test			
H_0: C(4)+C(7) = 0	H_0 rejected at 1% level		
H_0: C(4)+C(8) = 0	H_0 rejected at 1% level		
H_0: C(4)+C(9) = 0	H_0 rejected at 1% level		
H_0: C(4)+C(10) = 0	H_0 rejected at 1% level		
H_0: C(4)+C(11) = 0	H_0 rejected at 1% level		
H_0: C(4)+C(12) = 0	H_0 rejected at 1% level		
Heteroskedasticity test ARCH			
F-statistic	1.07	Prob. F(36,273)	0.37
Obs*R-squared	38.25	Prob. Chi-Square(36)	0.37

DISCUSSION

This study is an attempt to explore the day-of-the week effect in foreign exchange market volatility over the different volatility regimes. The literature on foreign exchange market anomaly has been not so extensive and most of them explored the presence of calendar anomalies in price changes. (McFarland *et al*., 1982) showed for eleven foreign exchange markets that the dollar denominated price changes are high on Mondays and Wednesdays and low on Thursdays and Fridays. This was re-examined and confirmed by So (1987). Evidence of calendar effect in the US currency market is also reported by Cornett *et al*. (1995). Hsieh (1988) considered five foreign currencies and showed that mean and variances are different across the days of the week. Bessembinder (1994) reported that the spot and forward market has significantly higher bid-ask spreads on Fridays and prior to holidays. This result was supported by Glassman (1987) while Breuer (1999) showed that although day of the week effect is present in the forward foreign exchange markets, it is statistically insignificant. Tang (1997) found that different days in week have significant impact on the diversification of foreign currency risk, especially on skewness and kurtosis. According to his results, both the skewness and kurtosis are unsystematic and they keep on changing, in both value and sign over different days in the week. Ke *et al*. (2007) found day-of-the-week effect in the first three days of the week for Taiwanese foreign exchange market. Hakan *et al*. (2007) found significant day-of-the-week-effect in the Turkish foreign exchange market. The day-of-the-week-effect has often been touted as a temporary, time-specific phenomenon. Yamori and Mourdoukow (2003) showed that although the day-of-the-week-effect was present in the Yen/US dollar exchange rate for the 1973-1989 period, it disappeared in the 1990s. This study was extended for 29 currencies Yamori and Kurihara (2004) and a similar result was found. The day-of-the-week effect was present throughout the 1980 in some of the 29 currencies against the US Dollar but it disappeared completely in the 1990. Occurrence of day-of-the-week-effect is also sometimes attributed to model mis-specification. Saadi *et al*. (2006) found that the day of the week effect in conditional variance for USD/CAD disappears completely when accounted for autocorrelation, heteroscedasticity and non-normality. The present study follows this line of exploration in the context of Indian Rupee-US dollar exchange rate. Studies in the context of calendar anomaly in the Indian foreign exchange market have been almost non-existent. Moreover, it is advancement over the existing literature in the sense that it has tried to relate the changing nature of calendar anomaly with the different volatility regimes. Although there is a vast literature regarding structural breaks in the stock markets, the studies in context of foreign exchange is comparatively smaller. However, a considerable amount of work has been carried out in order to understand the structural dynamics of the currency markets better. Most of the works has found evidences of structural break/s in the foreign exchange market. Studies by Bollen *et al.* (2000), Ozdemir and Olgun (2007) and Kasman and Ayhan (2006) for the Turkish market, Zeileis *et al.* (2010) for Indian and Chinese foreign exchange market, Kar and Sarkar (2006) for Rs/USD exchange rate have shown evidence of structural breaks in these markets. Wilfling (2009) found evidences of volatility regime switching in eleven currencies currencies in the run-up to the European Monetary Union. Kocenda (2005) studies eleven CEE countries and not only provided evidence of structural breaks but his findings also support the hypothesis that the structural changes were caused by exchange rate policies. Most foreign exchange rates are empirically found to have long memory. The phenomena of volatility persistence can be partially explained by structural change (Beine and Laurent, 2000; Morana and Beltratti, 2004; Choi *et al.*, 2010). The present study has combined two existing branch of literature to explore whether volatility in foreign exchange market is really affected by daily transaction mechanism and whether and how the calendar anomalies change with volatility regime switching. The study found strong presence of day-of-the week effect during the phases of high volatility. However, the Monday and Tuesday effects remained in all but one volatility regimes. While the other effects could be taken as time-specific and dependent on volatility of the market, Monday and Tuesday effects might be taken as the real calendar anomalies in the context of Indian Rupee-US Dollar exchange rate volatility.

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