A GARCH Analysis of Exchange Rate Volatility and the Effectiveness of Central Bank Actions

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Abstract

We study, with daily and monthly data sets, the impact on exchange rate level and volatility of conventional monetary policy measures such as interest rates, intervention and other quantitative measures, compared to Central Bank communication. Using dummy variables in the best of an estimated family of GARCH models, we find communication to be the most effective of all the CB instruments evaluated for the period of analysis. Quantitative interventions either have perverse effects or are reversed over a longer period. Intervention increases volatility, while changes in reserve requirements decrease volatility in the short period but raise it over time. Higher charges for liquidity injection decrease monthly volatility. Macroeconomic news decreases volatility, while the interest differential increases volatility in the short period. Policy variables also affect the exchange rate itself. CB communication and intervention effectively appreciates the exchange rate. Quantitative credit restrictions, higher interest differentials and policy lending rates depreciate the exchange rate. The reason maybe capital inflows reduce as prospects for the real economy worsen.

JEL codes: E52, E58, F31

Key words: exchange rate volatility, monetary policy, intervention, communication, GARCH

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1. Introduction

Research on monetary policy has seen exponential growth, but the rich and challenging experiences in emerging markets are still under explored. In this paper we estimate the best model in the family of autoregressive conditional heterosckedasticity (ARCH) and generalized ARCH (GARCH) models of exchange rate volatility, for the period following a maturing of Indian policy, money and FX markets. Then we insert policy dummies to study the impact on exchange rate level and volatility of conventional monetary policy measures such as interest rates, intervention and other quantitative measures, and compare them to Central Bank (Reserve Bank of India, RBI) communication[1].

This is a rich period to analyze since the movement towards freer markets implies a large range of policy instruments continue to be used. An assessment of their relative impact is a contribution towards understanding transition and to determining the way forward.

India has seen rapid development in markets, institutions and instruments of monetary policy in the past decade. A liquidity adjustment facility (LAF) has been introduced and the overnight inter-bank loan rate (the call money rate, CMR) has largely been kept in a band between two policy rates through injections and absorptions of liquidity (Ghosh and Bhattacharya, 2009). Monetary policy follows a multiple indicator approach, giving weight to both inflation and growth. The RBI is not formally independent, although a series of measures have given it greater independence after the liberalizing reforms of the early nineties[2]. But in a populous low per capita income democracy, inflation is a politically sensitive issue, leading to a rapid response to contain inflationary expectations. Even so, supporting development is also a primary aim. There is an indication, not a target, of expected inflation. The exchange rate is a managed float. The stated policy aim is to reduce volatility, while the level is market determined around fundamentals. This period has seen movement from a fixed exchange rate, relaxation of controls on the current account of the balance of payments, and partial capital account convertibility.

[1] Fišer and Horváth (2010) use policy dummies in an equation for exchange rate volatility, and Ghosh and Bhattacharya (2009) do so in a GARCH model of the money market.

[2] For example, there is no longer automatic financing of the fiscal deficit.

There are no restrictions on equity flows, and surges in inflows have created problems for monetary management. There is a current account deficit, but reserves crossed dollar 300 billion at a peak in 2008. At the same time, development of foreign exchange markets has been rapid. The average daily turnover in Indian FX markets, which was about US $3.0 billion in 1998-99, grew to US $48 billion in 2007-08, the fastest rate of growth among world markets BIS (2007). Growth in derivatives especially was strong, increasing to more than double spot transactions (Goyal, 2010).

The RBI is not at the point of the impossible trinity, where monetary policy becomes ineffective, since the exchange rate is not fixed, and the capital account is not fully open. But it is a challenge to address the needs of the domestic cycle while managing external shocks. An important question is the impact of policy rates on the exchange rates. If this is low then rate change can be targeted to the domestic cycle. Also larger FX market turnover and rapid market deepening makes standard intervention less effective. Therefore if signaling is effective, it gives valuable degrees of freedom for policy.

There is evidence of the effect of CB communication, largely for developed countries, surveyed in Blinder *et. al* (2008). They argue that communication makes monetary policy more effective by creating news or reducing noise when markets are not perfect, or when there is learning[3]. Since uncertainties are pervasive in emerging markets, communication should have a larger effect there. Goyal *et. al.* (2009) demonstrate this theoretically, and present some evidence for India in a study of strategic interaction between monetary policy and FX markets. Fišer and Horváth (2010) show that Czech National Bank communication tends to decrease exchange rate volatility using a GARCH framework. Our paper contributes to a growing literature on CB communication.

We find communication to be the most effective of all the CB instruments evaluated for the period of analysis. Quantitative interventions either have perverse effects or are reversed over a longer period. Intervention increases volatility, while changes in reserve

[3] Empirical literature studying CB communication has grown rapidly in the last decade, as conventional wisdom in CB circles changed from saying as little as possible to the importance and the art of managing market expectations. Communication has become an important part of monetary policy.

requirements decrease volatility in the short period but raise it over time. Higher charges for liquidity injection decrease monthly volatility. Macroeconomic news also decreases volatility, while the interest differential increases volatility in the short period. A caveat is, with the dummy variable technique, the comparative size of different actions cannot be controlled for, but the results do imply that communication channels should be used more. There is some evidence US monetary policy announcements impact domestic markets.

Since the exchange rate is a managed float we also test if policy dummies affect the exchange rate itself, and find evidence of this. CB communication and intervention effectively appreciates the exchange rate, while quantitative credit restrictions, higher interest differentials and policy lending rates depreciate the exchange rate.

The structure of the paper is as follows. After explaining data and methodology in Section 2, the empirical analysis is presented in Section 3, before Section 4 concludes.

2. Data and Methodology

We use both daily and monthly data. The daily data set is from 1st November 2005 to 31st December 2008, giving a total of 1157 observations. The monthly data set is from Jan 2002 to December 2008, that is, a total of 84 observations. Thus we have enough observations to carry out time series analysis both in the daily and in the monthly case. The monthly data period starts with the adoption of LAF, while the daily data period covers a time of large exchange rate volatility, when the LAF had reached greater maturity. The daily frequency is required since markets take several days to absorb news, while the monthly frequency picks up greater strategic interaction, feedback and simultaneity. Moreover, the RBI does not release high frequency intervention data, so that the impact of published intervention data can only be examined at the monthly frequency. Data sources are given in the appendix and are RBI, US Federal Reserve, Reuters, and Indian Ministry of Finance websites.

GARCH models for exchange rate returns at the monthly and daily frequency provide a measure of exchange rate volatility. A number of models were estimated by maximizing the log-likelihood through an iterative process. The best were selected based on diagnostics such as AIC, SIC[4], F-tests, and the Q test. The latter checks the null hypothesis that there is no remaining residual autocorrelation, for a number of lags, against the alternative that at least one of the autocorrelations is nonzero. The null is rejected for large values of Q. The best fitting models are given below.

ARCH (7) for daily data, implying that tomorrow's variance is dependent upon last 7 days or last week's volatility:

$$\Delta \ln ex_t = c + \chi \ln\left(\sigma_t^2\right) + \varepsilon_t \qquad \text{Mean equation}$$

$$\sigma_t^2 = \alpha + \beta \sum_{i=1}^{7} \varepsilon_{t-i}^2 + \delta_i \sum_{i=1}^{n} CB_{it} + \lambda_1 \, intdiff_t + \lambda_2 news_t \qquad \text{Variance equation}$$

AR (1) and GARCH (1,1) for the monthly data:

$$\Delta \ln ex_t = c + \phi \Delta \ln ex_{t-1} + \varepsilon_t \qquad \text{Mean equation}$$

$$\sigma_t^2 = \alpha + \beta \varepsilon_{t-1}^2 + \gamma \sigma_{t-1}^2 + \delta_i \sum_{i=1}^{n} CB_{it} + \lambda_1 \, intdiff_t \qquad \text{Variance equation}$$

Both these specifications make residuals and squared residuals white noise, so that no unmodelled autocorrelation is left in the data[5].

In the mean equation, for the first difference of the log exchange rate (a measure of exchange rate returns), the constant term *c* gives the average rate of depreciation or appreciation. Taking first differences eliminated a unit root in levels. With daily data arch-in-mean and with monthly data, a lagged dependent term is also required. The

[4] The lower are AIC and SIC the better the model, since the tests are based on the residual sum of squares.
[5] The nonnegativity restrictions on the parameters are very often violated in practice. The moment structure of an ARCH model is found to be too restrictive and the constraint becomes too complicated for higher order models. In some of the models we do get negative betas, but even so no other model fits the data well except arch 7. Even if some betas are negative (extremely small values) overall variance is positive. Non-linear models may be better able to tackle the problem compared to garch-egarch models.

conditional variance σ_t^2 of the error term ε_t is then specified by the ARCH or GARCH model. It includes a constant, lagged error variables (ARCH terms), lagged conditional variance (GARCH term), the interest differential ($intdiff_t$), and a number of variables capturing central bank actions (CB_{it}). The interest rate differential is defined as the difference between the Indian Call Money Rate and the US Federal Fund Rate.

Since an Indian policy objective is to reduce exchange rate volatility, including these monetary policy variables allows us to address the issue of how effective they are. That is, whether they have calming effect on exchange rate volatility or they further aggravate the volatility. With tick-by-tick data as CB intervention creates news, volatility can be expected to increase. But over longer periods it may be successful in achieving its objective. In mature markets, the exchange rate itself is expected to be a random walk around equilibrium levels. But in emerging markets with large reserve accumulation, the exchange rate regime is more properly a managed float. Thus, although affecting the exchange rate level is not a stated policy objective, we also test if our policy dummies affect the level of the exchange rate.

The daily specification includes a macroeconomic news variable ($news_t$). This was constructed as a dummy variable taking a value of unity on the days macroeconomic news on production or pricing is released on government and RBI websites.

The policy variables included in CB_{it} are:

$dvacrr_t$ - It is the dummy variable, which takes value 1 when any change in the cash reserve ratio (CRR), commercial bank reserves with the RBI, is announced by the RBI or is 0 otherwise.

$dvecrr_t$ –This dummy variable takes value 1 when CRR change effectively comes into force or is 0 otherwise.

dvintvnet$_t$-This dummy variable takes the value 1 whenever there is any intervention by the RBI and is 0 otherwise.

dvrep$_t$- This dummy variable takes the value 1 when the repo rate is changed. It is 0 otherwise. The repo rate, the upper bound of the liquidity adjustment facility (LAF) corridor, is the rate at which RBI lends in the LAF.

dvrev$_t$-This dummy variable takes the value 1 when the reverse repo rate is changed or is 0 otherwise. The reverse repo rate is the rate at which the RBI absorbs liquidity in the LAF, thus constituting the lower bound for the LAF.

fomc$_t$-This stands for the US federal open market committee meeting. Whenever this meeting takes place this dummy variable takes the value 1. It is 0 otherwise.

dvlafps$_t$- This takes value 1 whenever RBI resorts to liquidity adjustment facility or is 0 otherwise. *lafps*$_t$ is purchase minus sale in repo/ reverse repo auctions in LAF, that is, net injection (+) minus net absorption (-) of liquidity by RBI. We use it as an instrument for daily intervention because intervention changes domestic liquidity, which requires to be sterilized. Especially in our data period, inflows were high, and LAF absorption was also used to contribute to sterilization.

review$_t$- It takes value 1 whenever RBI reviews policy and is 0 otherwise. Prior to 2005, RBI used to review once in 6 months, after that the frequency was increased to once in three months.

speeches$_t$ - It is a categorical variable taking different values depending on which RBI top official has given a speech and when the comments on the economy or on policy were made. It takes the value 3 when the RBI governor gives a speech and 4 when this speech is given within a week before or after the meeting. It takes value 1 when any of the three deputy governors gives a speech and 2 when speech is given within one week before or after the meeting.

Table 1: Daily Descriptive Statistics									
	mean	**median**	**max**	**min**	**std dev**	**skewness**	**kurtosis**	**Jarque Bera test**	**probability**
$lnex_t$	3.77	3.79	3.92	3.67	0.06	0.01	-0.96	44.44	0
$fdiff_t$	0.003	0	1.2	-1.44	0.17	0.08	12.56	7528.54	0
$dvacrr_t$	0.009	0	1	0	0.09	10.63	111.19	612595.6	0
$dvecrr_t$	0.01	0	1	0	0.11	8.62	72.46	265227.7	0
$dvlafps_t$	0.66	1	1	0	0.47	-0.68	-1.54	203.21	0
$lafps_t$	-7074.32	-3000	91720	-79005	29114.57	0.15	0.44	8.62	0.01
$dvrev_t$	0.003	0	1	0	0.06	16.94	285.49	3950434	0
$dvrep_t$	0.01	0	1	0	0.10	9.68	91.83	420985.6	0
$speeches_t$	0.23	0	4	0	0.73	3.33	10.01	7483.92	0
$review_t$	0.01	0	1	0	0.10	9.68	91.83	420985.6	0
$news_t$	0.23	0	1	0	0.42	1.26	-0.42	326.18	0
$intdiff_t$	2.45	1.76	35.2	-5.15	3.87	3.55	25.34	33108.35	0
$fomc_t$	0.03	0	1	0	0.16	5.87	32.50	57075.3	0

Table 1 gives descriptive statistics for the daily data set. Mean of announcement of CRR change is lower than the mean of the effective implementation date. This is because implementation is over a longer period of time, normally in 2-3 stages. In the period of analysis, the repo rate was changed more often compared to the reverse repo rate. The call money rate on an average exceeded the federal fund rate by about 2.5% points. Since $lafps_t$ is negative, on an average liquidity was been sucked out of the economy for the period, indicating sterilization associated with accumulation of foreign currency. The frequency of RBI meetings is less than half that of $fomc_t$. The average frequency of RBI communication through speeches almost matches that of macroeconomic news. $fdiff_t$ is the first difference of the log exchange rate. The Jarqe-Bera test based on the 2nd and 3rd moments is large, showing severe non-normality, as is to be expected in daily data.

For monthly descriptive statistics (Table 2), as was the case in daily descriptive stats, mean of effective implementation of CRR change is higher than announcement. RBI's intervention on monthly basis is high implying that RBI constantly monitors the market and participates in it. Repo rate is the preferred monetary policy tool over reverse repo. Monthly call money rate is higher than federal fund rate by 2.82 percentage points.

Table 2: Monthly Descriptive Statistics										
	lnex $_t$	***dvecrr*** $_t$	***dvacrr*** $_t$	***dvintvnet*** $_t$	***dvrev*** $_t$	***dvrep*** $_t$	***invnet*** $_t$	***fdiff*** $_t$	***intdiff*** $_t$	***review*** $_t$
Mean	3.80	0.19	0.17	0.86	0.13	0.20	2120.90	7.46E-05	2.82	0.25
Median	3.81	0	0	1	0	0	1952.21	-0.002	3.08	0
Max	3.89	1	1	1	1	1	13625	0.07	8.81	1
Min	3.67	0	0	0	0	0	-18666	-0.04	-4.53	0
Std dev	0.06	0.40	0.37	0.35	0.34	0.40	4511.45	0.02	1.77	0.44
Skewness	-0.55	1.61	1.82	-2.08	2.23	1.51	-0.81	1.48	-0.87	1.18
Kurtosis	2.61	3.49	4.20	5.17	5.79	3.19	9.00	8.60	7.81	2.33
JarqueBera	4.67	35.62	49.84	74.76	94.21	30.86	115.77	137.51	81.35	20.22
Probability	0.10	0	0	0	0	0	0	0	0	0.00004

The correlation coefficients (Tables 3 and 4) among the policy variables are not very large, but naturally repo and reverse repo rate changes do tend to be clustered with the policy review meetings, and the correlations are larger at the monthly frequency. Large correlations imply multicollinearity in the regressions, making the results suspect[6]. Therefore we run regressions with the dummy variables singly, in clusters and all together.

Table 3: Daily Correlation Coefficients										
	dvacrr $_t$	***dvecrr*** $_t$	***dvlafps*** $_t$	***dvrev*** $_t$	***dvrep*** $_t$	***speeches*** $_t$	***review*** $_t$	***news*** $_t$	***intdiff*** $_t$	***fomc*** $_t$
dvacrr $_t$	1.00									
dvecrr $_t$	-0.01	1.00								
dvlafps $_t$	0.07	-0.16	1.00							
dvrev $_t$	-0.006	-0.007	0.04	1.00						
dvrep $_t$	0.27	-0.01	0.07	0.43	1.00					
speeches $_t$	0.06	-0.03	0.14	-0.02	0.003	1.00				
review $_t$	0.36	-0.01	0.07	0.28	0.33	-0.03	1.00			
news $_t$	-0.008	0.21	-0.32	0.002	0.02	-0.04	-0.02	1.00		
intdiff $_t$	0.10	0.03	-0.05	-0.01	0.09	0.0004	-0.02	0.02	1.00	
fomc $_t$	0.10	-0.02	0.10	-0.010	0.09	-0.04	0.09	-0.003	0.03	1.00

[6] If two variables are perfectly correlated, variance becomes infinity. So significance is low even R^2 is high, the results are dependent on the data set, and coefficients can have the wrong sign or size. Multicollinearity is a common problem when a large number of dummy variables are used.

Table 4: Monthly Correlation Coefficients							
	$dvecrr_t$	***$dvacrr_t$***	***$dvintvnet_t$***	***$dvrev_t$***	***$dvrep_t$***	***$intdiff_t$***	***$review_t$***
$dvecrr_t$	1.00						
$dvacrr_t$	0.31	1.00					
$dvintvnet_t$	0.18	0.16	1.00				
$dvrev_t$	0.04	-0.04	-0.33	1.00			
$dvrep_t$	0.23	-0.05	-0.31	0.33	1.00		
$intdiff_t$	0.16	0.02	0.32	0.02	0.16	1.00	
$review_t$	-0.06	0.18	-0.18	0.30	0.10	-0.23	1.00

3. Empirical Results and Analysis

Table 8 summarizes the policy instruments that are significant, and gives their signs. One cluster variable also reported is *$communication_t$*, which combines the two CB communication variables, *$speeches_t$* and *$review_t$*. The table also allows us to see how the monthly affect, which allows for policy feedback and simultaneity, differs from the shorter-run daily effect.

Although the stated aim of intervention is to decrease volatility, the intervention dummy has a positive sign suggesting that RBI activity in the FX market actually increased volatility[7]. This result is not robust, however, because the use of binary variables cannot capture the intensity of intervention, or control for simultaneity. Thus the positive sign may be a result of the RBI intervening in times of high volatility. Regressions with the actual value of intervention may well give it a negative effect on volatility. It may also be a consequence of the period of analysis, which had unusually high volatility since it includes the global crisis period with large outflows. FX market turnovers were also steadily increasing over the period, reducing the relative size of intervention. Most studies of an earlier period find that RBI intervention decreases volatility (Edison et. al., 2007, Pattanaik and Sahoo, 2003, Goyal[8] et. al., 2009). But Goyal et. al.(2009) also find that daily FX market turnover increases with RBI intervention[9].

[7] The proxy for daily intervention, *$lafps_t$*, created instability and had to be dropped.
[8] While the earlier two studies use OLS, this study uses GMM, controlling for simultaneity.
[9] Fratzsher (2004) finds communication can be either a complement or a substitute for intervention.

$$\sigma_t^2 \geq 0,\ 0 < \beta_i\text{'s} < 1$$

$$\Delta \ln ex_t = c + \chi \ln(\sigma_t^2) + \varepsilon_t \qquad \sigma_t^2 = \alpha + \beta_i \sum_{i=1}^{7} \varepsilon_{t-i}^2 + \delta_i \sum_{i=1}^{7} CB_{it} + \lambda_1 \operatorname{int} diff_t + \lambda_2 news_t$$

Table 5: Estimating exchange rate volatility and policy actions with daily data

	1	**2**	**3**	**4**	**5**	**6**
C	0.124***	0.011	0.087***	0.080***	0.096***	-0.005
	(0.004)	(0.014)	(0.017)	(0.017)	(0.016)	(0.018)
χ	0.026***	0.003	0.018***	0.016***	0.020***	-0.001
	(0.017)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
α	0.006***	0.007***	0.006***	0.005***	0.005***	0.009***
	(0.0004)	(0.0005)	(0.0003)	(0.0004)	(0.0003)	(0.001)
β_1	0.224***	0.284***	0.265***	0.289***	0.307***	0.209***
	(0.028)	(0.035)	(0.031)	(0.033)	(0.034)	(0.029)
β_2	0.017**	0.020***	0.010**	0.011**	0.015**	0.021***
	(0.007)	(0.007)	(0.005)	(0.005)	(0.006)	(0.008)
β_3	-0.007	0.003	-0.005	0.010	0.012	0.010**
	(0.007)	(0.008)	(0.004)	(0.009)	(0.008)	(0.009)
β_4	0.054***	0.051***	0.071***	0.066***	0.056***	0.042***
	(0.007)	(0.007)	(0.009)	(0.008)	(0.007)	(0.007)
β_5	0.011	0.020	-0.016**	-0.016**	0.039***	0.032**
	(0.012)	(0.014)	(0.008)	(0.007)	(0.014)	(0.014)
β_6	0.191***	0.186***	0.269***	0.247***	0.191***	0.149***
	(0.021)	(0.024)	(0.026)	(0.024)	(0.021)	(0.020)
β_7	0.300***	0.360***	0.334***	0.338***	0.317***	0.191***
	(0.038)	(0.053)	(0.042)	(0.041)	(0.039)	(0.026)
$\delta_1(dvacrr_t)$	-0.004	-0.007***			0.0009	
	(0.004)	(0.0005)			(0.003)	
$\delta_2(dvecrr_t)$	-0.002	-0.007***			-0.004***	
	(0.002)	(0.0005)			(0.001)	
$\delta_3(dvrev_t)$	-0.002		0.004			
	(0.023)		(0.034)			
$\delta_4(dvrep_t)$	-0.003		-0.006***			
	(0.003)		(0.0003)			
$\delta_5(speeches_t)$	-0.001			-0.001		-0.001***
	(0.001)			(0.0005)		(1.86E-05)
$\delta_6(review_t)$	-0.007**			-0.005***	-0.005**	
	(0.003)			(0.0004)	(0.002)	
$\delta_7(fomc_t)$	0.006***					
	(0.001)					
$\lambda_1(intdiff_t)$	0.0003***			0.0003***		0.001***
	(0.0001)			(9.50E-05)		(8.84E-06)
$\lambda_2(news_t)$	-0.003***					-0.006***
	(0.001)					(0.001)
L-B(10), RES	12.743	11.830	13.029	10.826	13.044	10.839
L-B(10), SQR RES	3.131	4.419	4.238	3.272	2.257	8.526
SIC	-1.206	-1.229	-1.224	-1.241	-1.233	-1.224
N	1157	1157	1157	1157	1157	1157

Note: Standard errors (in parentheses), Ljung Box Q-statistics of the tenth lag of residuals and squared residuals are reported. ***,** and * denotes significance at 1%,5% and 10% level.

Table 6: Individual testing of daily dummy variables			
	1	**2**	**3**
c	-0.011 (0.011)	0.011** (0.005)	0.071*** (0.016)
χ	-0.002 (0.002)	0.001 (0.001)	0.015*** (0.004)
α	0.003*** (0.0002)	0.005*** (0.0003)	0.005*** (0.0003)
β_1	0.356*** (0.031)	0.302*** (0.027)	0.315*** (0.035)
β_2	0.008** (0.004)	0.011** (0.004)	0.016** (0.006)
β_3	0.037*** (0.007)	0.023*** (0.007)	0.020** (0.009)
β_4	0.057*** (0.008)	0.057*** (0.007)	0.058*** (0.008)
β_5	-0.018** (0.007)	-0.015*** (0.002)	0.043*** (0.015)
β_6	0.241*** (0.023)	0.276*** (0.023)	0.178*** (0.020)
β_7	0.485*** (0.053)	0.436*** (0.046)	0.317*** (0.039)
δ_6(*review$_t$*)			-0.005*** (0.0005)
λ_1(*intdiff$_t$*)	0.0003*** (6.66E-05)		
λ_2(*news$_t$*)		-0.003*** (0.0003)	
L-B(10), RES	9.781	-1.294	12.184
L-B(10), SQR RES	4.136	3.399	2.662
SIC	-1.270	-1.294	-1.249
N	1157	1157	1157

Note: Standard errors (in parentheses), Ljung Box Q-statistics of the tenth lag of residuals and squared residuals are reported. ***,** and * denotes significance at 1%,5% and 10% level.

In informal conversations, FX dealers, often suggest that RBI intervention can increase FX market activity. Asymmetric information means that dealers, who anticipate RBI action and its effect on the exchange rate, would use this to buy or sell, making money at the expense of less informed market participants. Any shock to markets would increase expected returns and therefore volatility, as new information comes in, in high frequency data capturing actual trades. This is the creating news function of CB action. But studies show that in longer horizons the effect can be in either direction (Blinder et. al, 2008). In the long run no news remains unprocessed.

$$\Delta \ln ex_t = c + \phi \Delta \ln ex_{t-1} + \varepsilon_t \qquad \sigma_t^2 = \alpha + \beta \varepsilon_{t-1}^2 + \gamma \sigma_{t-1}^2 + \delta_i \sum_{i=1}^{n} CB_{it} + \lambda_1 \operatorname{int} diff_t$$

$$0 < |\phi| < 1 \text{ , } \alpha > 0,\ \beta \geq 0,\ \gamma \geq 0,\ \beta + \gamma < 1, \sigma_t^2 \geq 0$$

Table 7: Estimating exchange rate volatility and policy actions with monthly data

	1	**2**	**3**	**4**	**5**	**6**
c	-0.003*	-0.002	-0.0009	-0.001	-0.001	-0.001
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)
Φ	0.02	0.48***	0.53***	0.28**	0.20	0.34***
	(0.15)	(0.15)	(0.13)	(0.11)	(.17)	(0.11)
α	8.38E-05	1.23E-05**	2.77E-05***	-3.38E-05***	0.0001***	1.02E-06***
	(0.0001)	(5.23E-06)	(7.95E-06)	(6.25E-07)	(5.38E-05)	(2.89E-06)
β	0.14	0.39***	0.61***	0.05	0.15	-0.06
	(0.15)	(0.13)	(0.20)	(0.05)	(0.11)	(0.04)
γ	0.58	0.58***	0.22**	1.04***	0.48***	1.12***
	(0.36)	(0.10)	(0.10)	(0.05)	(0.19)	(0.03)
δ_1*(dvacrr$_t$)*	1.69E-06		0.0005**			
	(3.91E-05)		(0.0002)			
δ_2*(dvecrr$_t$)*	-7.50E-05	0.0001***				
	(4.48E-05)	(4.11E-05)				
δ_3*(dvintvnet$_t$)*	-4.03E-05			3.45E-05***		
	(0.0001)			(2.74E-07)		
δ_4*(dvrev$_t$)*	-4.46E-05					
	(3.06E-05)					
δ_5*(dvrep$_t$)*	1.52E-05				-0.0001**	
	(3.43E-05)				(6.31E-05)	
δ_6*(review$_t$)*	-3.38E-06					-2.15E-06***
	(2.33E-05)					(4.96E-07)
δ_7*(intdiff$_t$)*	7.66E-05**					
	(3.53E-05)					
L-B(10), RES	15.68	8.26	10.47	7.90	9.13	11.45
L-B(10), SQR RES	5.37	4.68	2.50	5.91	8.52	5.82
SIC	-5.70	-5.66	-5.66	-5.65	-5.37	-6.16
N	84	84	84	84	84	84

Note: Standard errors (in parentheses), Ljung Box Q-statistics of the tenth lag of residuals and squared residuals are reported. ***,** and * denotes significance at 1%,5% and 10% level.

But another interesting result that supports the limitations of quantitative instruments is the reversal of short-term impact, even if it is effective. Thus in the daily regressions the two CRR instruments decrease volatility, but each individually increases volatility in the longer period. Thus in the longer period markets may be able to get around restrictions, and overreact. Announcements tend to work individually in the longer run, but work only together with implementation in the short-run.

The interest differential, which represents arbitrage opportunities and therefore induces markets to create liquidity, raises volatility in the short period but is insignificant in the longer horizon. This may be because Indian regulatory restrictions on bank arbitrage are more effective in the longer period.

The LAF rates have no effect in daily regressions, but the repo rate at which the RBI lends, and which therefore affects the cost of liquidity, reduces volatility in the short and the longer period.

Across all the regressions, and time periods, we find RBI communication decreases volatility[10]. With daily data $news_t$ decreases volatility but $intdiff_t$ increases it. Although $speeches_t$ alone are not significant but $speeches_t$, $news_t$ and $intdiff_t$ all significant together. The $speeches_t$ dummy includes weights for when it is made and who makes it. Its significance therefore suggests that both timing and source matter. The $news_t$ and $speeches_t$ variables could not be constructed for the monthly frequency, but at the monthly frequency (Table 7, column 6) $review_t$ is significant when taken singly.

Table 8: Significant Impact of Monetary Policy Instruments on Volatility

Monetary Policy Instrument	**Daily**	**Monthly**
$dvacrr_t$	negative	positive
$dvecrr_t$	negative	positive
$dvrep_t$	negative	negative
$dvinvnet_t$		positive
$intdiff_t$	positive	positive
$news_t$	negative	
crr	negative	
$communication_t$	negative	

Regressions with all the dummy variables may be subject to multicollinearity, and so should be interpreted with care. But even those results (although they are not reported in Table 8) generally support the coefficients in Table 8. In the daily regression (Column 1, Table 5) only $review_t$, $news_t$, $fomc_t$ and $intdiff_t$ are significant. The first two reduce volatility, while the second two increase it.

[10] Although $review_t$ is insignificant with all dummy variables taken together, multicollinearity reduces the reliability of this result. Singly it is negative and significant.

Although $fomc_t$ is not significant alone, its significance with all the dummy variables gives only limited support to Indian policy makers' worry that markets get too much influenced by US policy. That timing matters as part of the $speeches_t$ variable implies RBI's future course of action triggers expectations and market actions.

Although traditionally news is supposed to increase volatility in markets, Fišer and Horváth (2010) find that it reduces volatility in Czech Republic. They argue that since information is scarce in emerging markets news calms them. In our study also the sign of the coefficient on news is consistently negative. In emerging markets the reducing noise function of CB communication may be dominating the creating news function. In our study it turns out to be the most consistently effective in reducing volatility of the various instruments tested. It may also reflect the credibility of the CB and the weight given to its pronouncements, given its strong balance sheet, and reserves.

The results from putting the dummy variables in the mean equation are reported in Tables 9 and 10 for daily and monthly data respectively. The equations estimated in each case are reported above the tables. Many of the dummy variables turn out to be significant in both the regressions, implying that policy in India does affect the level of the exchange rate.

With daily data $review_t$ is significantly negative, strongly appreciating the exchange rate, while $fomc_t$ with a positive coefficient depreciates it. $Dvrep_t$ also strongly appreciates the exchange rate, while $dvrev_t$ and $dvacrr_t$ are weakly positive. With the monthly dataset $dvintvnet_t$ strongly appreciates the exchange rate; $intdiff_t$ significantly depreciates it as do the crr variables; $dvecrr_t$ is strongly significant and $dvacrr_t$ is weakly significant. While $dvintvnet_t$ has the opposite effect to the stated policy intention on volatility it effectively appreciates the exchange rate. Quantitative credit restrictions, higher interest differentials and policy lending rates maybe worsening prospects of the real economy, therefore reducing capital inflows and depreciating the exchange rate.

$$\Delta \ln ex_t = c + \delta_i \sum_{i=1}^{8} CB_{it} + \lambda_1 \operatorname{int} diff_t + \lambda_2 news_t + \chi \ln(\sigma_t^2) + \varepsilon_t \qquad \sigma_t^2 = \alpha + \beta_i \sum_{i=1}^{7} \varepsilon_{t-i}^2$$

Table 9: Estimating mean exchange rates and policy actions with daily data

	1	2	3	4	5	6
c	0.012 (0.024)	0.0004 (0.011)	-0.022*** (0.008)	-0.030*** (0.009)	0.008 (0.009)	-0.01 (0.01)
χ	0.002 (0.003)	-0.0002 (0.002)	-0.004*** (0.002)	-0.006*** (0.002)	0.001 (0.002)	-0.003 (0.002)
α	0.003*** (0.0003)	0.003*** (0.0002)	0.002*** (0.0002)	0.002*** (0.0002)	0.003*** (0.0002)	0.003*** (0.002)
β_1	0.387*** (0.037)	0.396*** (0.031)	0.378*** (0.029)	0.375*** (0.029)	0.38*** (0.03)	0.38*** (0.03)
β_2	0.015*** (0.005)	0.007** (0.003)	0.005* (0.003)	0.005 (0.003)	0.008** (0.004)	0.008** (0.004)
β_3	0.038*** (0.010)	0.045*** (0.007)	0.055*** (0.007)	0.051*** (0.007)	0.04*** (0.007)	0.05*** (0.007)
β_4	0.054*** (0.008)	0.062*** (0.008)	0.049*** (0.007)	0.049*** (0.007)	0.06*** (0.008)	0.05*** (0.007)
β_5	0.056*** (0.014)	-0.018*** (0.002)	-0.014*** (0.005)	-0.014*** (0.002)	-0.02*** (0.004)	-0.02*** (0.005)
β_6	0.211*** (0.024)	0.273*** (0.023)	0.255*** (0.023)	0.247*** (0.023)	0.28*** (0.02)	0.26*** (0.02)
β_7	0.463*** (0.056)	0.478*** (0.053)	0.680*** (0.067)	0.706*** (0.065)	0.47*** (0.05)	0.60*** (0.06)
$\delta_1(dvacrr_t)$	0.049* (0.027)					
$\delta_2(dvecrr_t)$	0.005 (0.930)					
$\delta_3(dvrev_t)$	0.163* (0.094)	0.137* (0.079)				
$\delta_4(dvrep_t)$	-0.014 (0.029)	-0.076*** (0.027)			-0.06** (0.03)	
$\delta_5(speeches_t)$	-0.004 (0.003)		-0.003 (0.002)			
$\delta_6(review_t)$	-0.091*** (0.023)		-0.097*** (0.019)	-0.094*** (0.019)		-0.08*** (0.02)
$\delta_7(fomc_t)$	0.014 (0.011)		0.033*** (0.009)	0.035*** (0.009)		
$\delta_8\,(dvlafps_t)$	-0.0003 (0.021)					
$\lambda_1(intdiff_t)$	-9.82E-05 (0.001)			-0.0001 (0.001)		
$\lambda_2(news_t)$	-0.007 (0.007)					
L-B(10), RES	8.472	11.351	10.336	10.596	10.594	10.586
L-B(10), SQR RES	3.926	3.846	4.459	4.499	3.873	4.354
SIC	-1.221	-1.270	-1.267	-1.266	-1.270	-1.276
N	1157	1157	1157	1157	1157	1157

Note: Standard errors (in parentheses), Ljung Box Q-statistics of the tenth lag of residuals and squared residuals are reported. ***,** and * denotes significance at 1%,5% and 10% level.

$$\Delta \ln ex_t = c + \phi \Delta \ln ex_{t-1} + \delta_i \sum_{i=1}^{5} CB_{it} + \lambda_1 \operatorname{int} diff_t + \varepsilon_t \qquad \sigma_t^2 = \alpha + \beta \varepsilon_{t-1}^2 + \gamma \sigma_{t-1}^2$$

Table 10: Estimating mean exchange rates and policy actions with monthly data

	1	**2**	**3**	**4**
c	-0.002 (0.002)	0.001*** (0.0002)	-0.003 (0.003)	-0.010*** (0.003)
ϕ	0.343*** (0.097)	0.261** (0.129)	0.392*** (0.130)	0.532*** (0.107)
α	7.97E-07 (1.11E-06)	7.87E-07 (6.12E-07)	1.13E-05* (6.64E-06)	2.04E-05*** (4.93E-06)
β	-0.075*** (0.023)	-0.054*** (0.019)	0.548*** (0.190)	1.123*** (0.424)
γ	1.122*** (0.057)	1.105*** (0.035)	0.605*** (0.128)	0.111 (0.136)
δ_1***(dvacrr$_t$)***			0.005* (0.003)	
δ_2***(dvecrr$_t$)***			0.006** (0.003)	
δ_3***(dvintvnet$_t$)***		-0.003*** (0.001)		0.001 (0.003)
δ_4***(dvrev$_t$)***				
δ_5***(dvrep$_t$)***				
λ_1	0.0001*** (2.71E-05)			0.002*** (0.0003)
L-B(10), RES	14.978	9.990	7.805	16.213
L-B(10), SQR RES	6.747	7.287	3.190	3.868
SIC	-6.398	-6.032	-5.606	-6.203
N	84	84	84	84

Note: Standard errors (in parentheses), Ljung Box Q-statistics of the tenth lag of residuals and squared residuals are reported. ***,** and * denotes significance at 1%,5% and 10% level.

4. Conclusion

In our tests of policy actions on exchange rate volatility, using policy dummies in a GARCH framework, communication outperforms more traditional policy variables. This may be a consequence of the steady deepening of FX and money markets so that quantitative interventions are a small share of total market transactions, while communication serves as a focal point, coordinating the actions of market participants (Sarno and Taylor, 2001). Given that the stated CB objective is to reduce volatility, quantitative actions have perverse effects. News also tends to calm markets, suggesting that in emerging markets news may be at less than optimal levels. This greater uncertainty, combined with the credibility of the CB, makes CB communication particularly effective. Policy variables also affect the exchange rate itself. CB communication and intervention effectively appreciates the exchange rate. Quantitative credit restrictions, higher interest differentials and policy lending rates depreciate the exchange rate. The reason maybe capital inflows reduce as prospects for the real economy worsen. The communication channel needs to be further studied, developed, and used more intensively.

Appendix: Data sources

Interest rate differential- www.rbi.org.in and www.federalreserve.gov

Repo rate- www.reuters.com

Reverse rep rate- www.reuters.com

Cash reserve ratio (Announcement + effective implementation)- www.rbi.org.in

Liquidity adjustment facility-www.rbi.org.in

Speeches-www.rbi.org.in press releases

Timing-www.rbi.org.in archives

Federal open market committee meetings-www.federalreserve.gov

Macroeconomic news- www.mospi.nic.in

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