Indian Currency Market Risk Analysis: Value-at-Risk Approach

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Emphasizing the need for risk mitigation arising out of excess volatility in rupee experienced by India post implementation of the market determined exchange rate regime in 1993, currency futures were introduced in India in 2008, and currency trading has become one of the most important financial operations since then. In this paper, an attempt has been made to measure and compare the market risk prediction ability of historical simulation, Monte-Carlo simulation, Exponentially Weighted Moving Average (EWMA) and linear parametric VaR approaches for Indian currency spot and futures market. Using the data from 2008 to 2013, the VaR associated with the three main currencies in the economy, namely, US dollar, euro and UK pound sterling, is calculated. Conditional and unconditional coverage tests have been applied to backtest the results of various VaR approaches. The results indicate that Monte-Carlo simulation is appropriate in predicting market risk. Further, it is also found that risk seems to be higher in the future market as compared to the underlying markets.

Introduction

An important structural change was brought in the Indian foreign exchange market when India moved from pegged exchange rate to market determined exchange rate regime in 1993. The demise of the system of fixed exchange rates added to financial risks (Jorion, 2000). Since then India has been experiencing high volatility in rupee. Emphasizing the need for risk mitigation arising out of excess volatility and also to advance Indian foreign exchange market to international standards (Somnath, 2011), currency futures were introduced in India in 2008, and currency trading has become one of the most important financial operations. Currency futures trading in INR-USD started on August 29, 2008. The exchange traded currencies were extended to the INR-Euro, INR-GBP and INR-Yen currency pairs in January, 2010. Derivatives instruments are introduced with the intention of reducing volatility and speculation in the underlying markets. But too much speculation in either of the markets would give rise to market risks. The serious limitation for a statistically significant analysis is the short histories of data of the developing economies (Goran *et al.*, 2010) like India. This paper attempts to measure and compare the market risk prediction ability of historical

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simulation, Monte-Carlo simulation, Exponentially Weighted Moving Average (EWMA) and linear parametric Value-at-Risk (VaR) approaches in Indian currency spot and futures market.

This paper is structured as follows: it presents a review of literature on various VaR methods and evaluation criteria, followed by the discussion of the methodology used in the study. Subsequently, the results are discussed, and finally, the conclusion is offered.

Literature Review

Don and Stuart (2002) measured and evaluated the performance of parametric and nonparametric VaR methods using a portfolio based on the foreign exchange exposure of a small open economy, Ireland, among its key trading partners. The results suggest that the orthogonal GARCH model is the most accurate method, while the EWMA specification is the more conservative approach. Golaka and Reddy (2003) used variance-covariance (normal) methods, including risk-metric, historical simulation and tail-index based approach, on daily exchange rate of rupee for the period 1993-2003 and concluded that the models considered failed in forecasting the expected losses and underestimated the risk. Further, Povilas *et al.* (2009) showed variance-covariance risk model to be better for the EUR/USD currency pair and revealed that the critical margin of 5% deviation was not over-passed.

In a more recent study, Ousama *et al.* (2012) compared four VaR models, namely, historical simulation, variance-covariance, Monte-Carlo and bootstrapping approaches applied to three currencies, Tunisian dinar/euro, Tunisian dinar/USD and Tunisian dinar/yen, and four currency portfolios in the Tunisian exchange for a period 1999-2007 and concluded that variance-covariance model produces appropriate estimates. Raúl *et al.* (2013) applied Generalized Extreme Value Distribution (GEVD) model for Peso/Dollar exchange rate. The results confirm the potential of the GEVD in explaining the extreme behavior of exchange rates. Dimitrios *et al.* (2014) compared parametric and nonparametric VaR methods for four asset classes, equity, forex, fixed income and commodity, and found that statistical accuracy and regulatory compliance essentially improved when quantile methods are used which account for the fat tails and the asymmetry of the innovations distribution. In particular, empirical analysis gives evidence in favor of the skewed Student *t*-distribution and the Extreme Value Theory (EVT) method. Jonathan *et al.* (2014) addressed market risk prediction for high frequency foreign exchange rates under nonlinear risk scaling behavior using the modified version of the Multifractal Model of Asset Returns (MMAR) for EUR/USD spot quotes. The study compared MMAR to historical simulation and GARCH(1, 1) and found that MMAR is a parsimonious model which produces admissible VaR forecasts at 12 h forecast horizon.

Data and Methodology

In this study, daily closing prices of spot and future currency pairs of USD, euro and GBP pound sterling traded on National Stock Exchange are analyzed. The data for the period from 2008 to 2013 was obtained from Bloomberg data source. The spot and future daily closing prices of the USD are collected for the period August 2008 till December 2013, while that of euro and GBP ranges from February 2010 to December 2013. Daily logarithmic returns are calculated for each of the currency pairs for further analysis using the following formula:

$$r_t = \ln\left(\frac{I_t}{I_{t-1}}\right) \times 100$$

where r_t is the currency returns and I_t is the exchange rate at time *t*.

In this paper four models for measuring the VaR, namely, Student *t* linear VaR, historical simulation, Monte-Carlo simulation and EWMA, are employed.

Student *t* linear VaR (Alexander, 2010) is useful when VaR is estimated over a short risk horizon, as positive excess kurtosis can be pronounced over a period of a few days or even weeks. The Student *t* density has a lower peak than the standard normal density, and it converges to the standard normal density as $\upsilon \rightarrow \infty$.

$$Students\ t\, VaR_{\alpha,\upsilon} = \sqrt{\upsilon^{-1}(\upsilon-2)}\, t_{\nu}^{-1}(1-\alpha)\sigma - \mu$$

The α quantile of the standard Student *t* distribution is denoted by $t_{\nu}^{-1}(a)$. To apply a Student *t* linear VaR formula to the portfolio, we need to use the quantiles from a generalized Student *t* distribution. The distribution is symmetric about a mean zero. The degrees of freedom parameter υ is estimated by fitting the distribution using Maximum Likelihood Estimation (MLE).

Historical simulation (Das, 2006) takes into account the past performance of the portfolio assuming that past is a good indicator of the near future. This method requires a long history of returns in order to get a meaningful VaR. Under this method, VaR is estimated as follows:

$$VaR_t(\alpha) = F^{-1}(\alpha)r$$

where $F^{-1}(\alpha)r$ is the q^{th} quantile $(1 - \alpha)$ of the sample distribution. This method does not make any assumption of the return distributions of the assets in the portfolio. But it suffers from serious limitations[1]. First, it relies completely on historical dataset and its idiosyncrasies. Second, it fails to accommodate changes in the market structure. Third, this method may not be computationally efficient when the portfolio contains complex securities or a very large number of instruments. Finally, it fails to handle sensitivity analyses.

Monte-Carlo VaR can be applied with any assumed distribution for risk factor returns. Under this method, VaR is determined in the same manner as historical simulation, but based on simulated sample (Hao *et al.*, 2011-12). Unlike other methods, Monte-Carlo simulation makes explicit the sampling variability in the risk numbers. Although, Monte-

[1] https://www.jpmorgan.com/tss/General/Risk_Management/1159369485859

Carlo simulation can be time-consuming according to the properties of problem, the main benefit of running it is that it can model instruments with nonlinear and path-dependent payoff functions, especially complex derivatives.

Exponentially weighted moving average is a typical technique for the calculation of volatility that was proposed by Morgan (1996). It is given by the following formula:

$$\sigma_t^2 = 0.006 \in_{t-1}^2 + 0.94\sigma_{t-1}^2$$

Backtesting VaR

Whatsoever VaR is calculated using the various methods, it can be reliable only when it is considered as accurate and has the predictive ability of capturing future market risk. This can be verified through backtesting (Nieppola, 2009). Backtesting is the process of comparing VaR estimates with the actual returns. It helps in detecting weaknesses in the models and points to the areas of improvements. Backtesting may be conditional or unconditional. Various backtesting methods that are used are BCBS's (1996) traffic light approach, Kupie's (1995) proportion of failures test, Christofferssen's (1998) interval forecast test, and unconditional coverage test. An unconditional coverage test involves testing of the null hypothesis that the indicator function, which is assumed to follow an i.i.d. Bernoulli process, has a constant 'success' probability equal to the significance level of VaR, α. The test statistic is a likelihood ratio statistic given by the following formula:

$$LR_{uc} = \frac{\pi_{\exp}^{n_1}\left(1-\pi_{\exp}\right)^{n_0}}{\pi_{obs}^{n_1}\left(1-\pi_{obs}\right)^{n_0}}$$

where $\pi_{\exp}$ is the expected proportion of exceedances = α; π_{obs} is the observed proportion of exceedances = $n_1/n; n_1$ is the observed number of exceedances; $n_0 = n - n_1$, where n is the same sample size of the backtest, n_0 is the number of returns with indicator 0.

A test for independence of exceedances is based on the formalization of the notion that when exceedances are not independent the probability of an exceedance tomorrow, given there has been an exceedance today, is no longer equal to α. The independence test statistic, derived by Christofferssen (1998) is as follows:

$$LR_{ind} = \frac{\pi_{obs}^{n_1}\left(1-\pi_{obs}\right)^{n_0}}{\pi_{01}^{n_{01}}\left(1-\pi_{01}\right)^{n_{00}}\pi_{11}^{n_{11}}\left(1-\pi_{11}\right)^{n_{10}}}$$

A combined test for both unconditional coverage and independence is the conditional coverage test. It is given by $LR_{cc} = LR_{uc} + LR_{ind}$

Results and Discussion

Using the data from 2008 to 2013, the study calculates the VaR associated to the three main currencies in the economy, namely, USD, euro and UK pound sterling. Table 1 presents the descriptive statistics of daily returns. The maximum average returns and high standard deviations are seen in future returns of all euro and GBP currency pairs than in their spot returns. This indicates that euro and GBP futures market are riskier than USD futures market. Excess kurtosis statistics of all the currency pairs indicate that the distributions have a much thicker tail. The coefficient of skewness indicates that all the series have asymmetric distributions skewed to the right. Further, it is evident from the Jarque-Bera statistics that none of the series is normally distributed.

Table 1: Descriptive Statistics

	EFR	ESR	GFR	GSR	USR	UFR
Mean	0.000291	0.000288	0.000325	0.000319	0.000264	0.000267
Median	0.000288	0.000530	0.000440	0.000375	0.000167	0.000142
Maximum	0.069984	0.039378	0.067705	0.035637	0.039038	0.032879
Minimum	–0.049769	–0.038292	–0.044955	–0.028833	–0.032938	–0.032657
SD	0.007319	0.006739	0.006710	0.006482	0.006214	0.006097
Skewness	0.601086	0.094800	0.777588	0.028443	0.103550	0.124685
Kurtosis	15.21381	6.098220	16.26866	4.721818	6.603853	5.920306
Jarque-Bera	6075.107	388.6083	7570.356	125.8881	700.3973	461.7324
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Observations	968	968	1,018	1,018	1,290	1,290

Figure 1 shows the logarithmic returns of the various currency pairs. High fluctuations of USD spot and future values are seen in third and fourth quarter in 2013. Fluctuations in log returns for USD spot and futures market were least during the period 2011. GBP futures and euro futures show stability in returns except at the end of 2011. Figure 2 shows the histogram of daily returns along with theoretical Gaussian and Student *t* probability density function. It is evident from the figure that Student's *t* fits the return distribution better than the Gaussian or normal distribution. The presence of tails heavier than the Gaussian is confirmed by the QQ plots of all the series in Figure 3.

Comparing Value-at-Risk Models Forecasting

The VaR of a portfolio is the maximum loss expected to occur with a certain probability over a given time period. This study assesses the performance of historical simulation, Monte-Carlo simulation, EWMA and parametric VaR. It is considered that VaR method generates accurate estimates if the null hypothesis that the VaR estimate is accurate is not rejected by any test (Pilar and Sonia, 2012). There is no unanimous agreement regarding which VaR models should be preferred. Several papers have found that the performance of the model depends on the sample size (Greg *et al.,* 2003). As the sample size increases, the forecast becomes more accurate. The one-day VaR estimates for all the methods implemented are presented in Table 2. VaR estimation is calculated at 90%, 95% and 99% confidence intervals.

Figure 1: Currency Pairs Logarithmic Returns

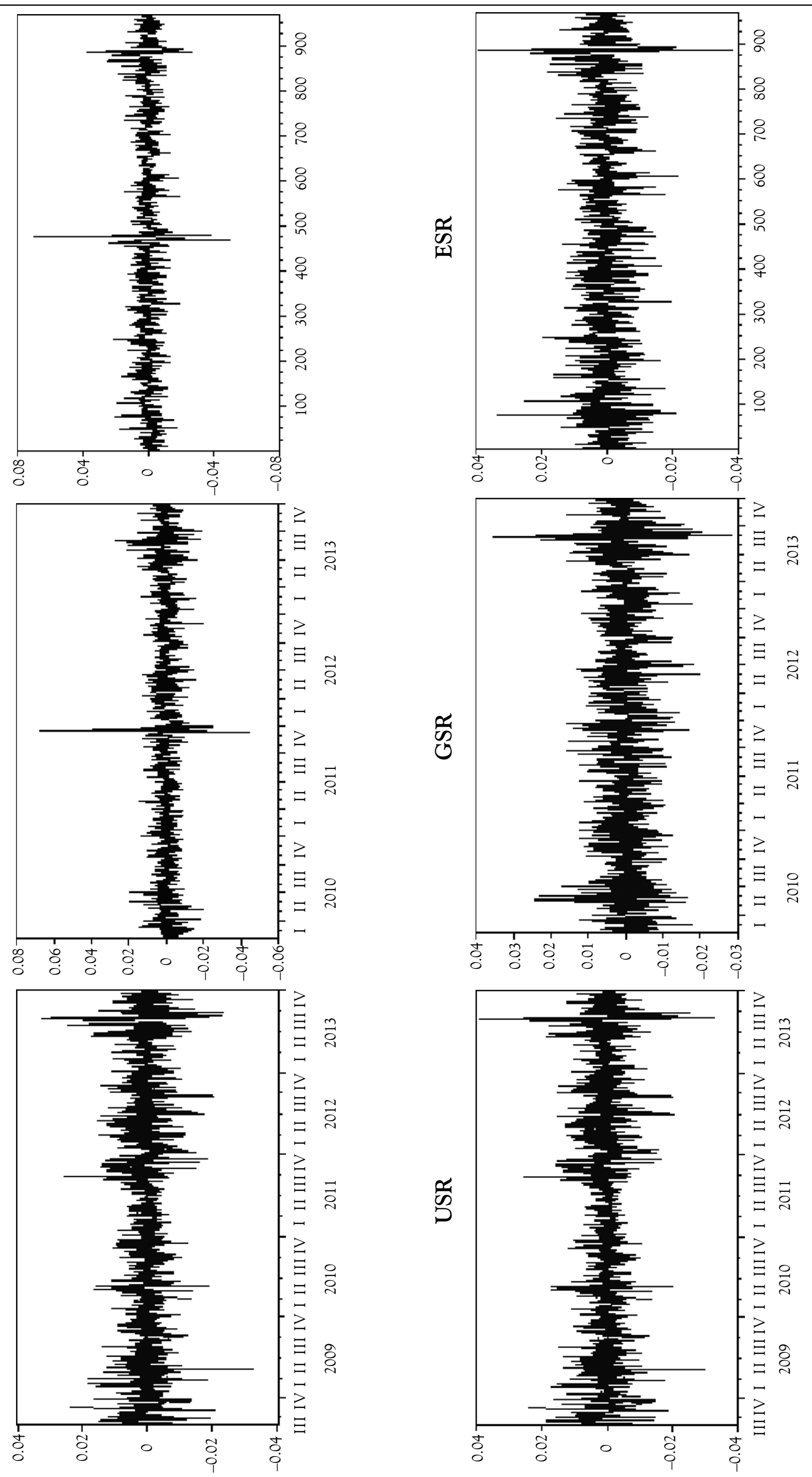

Figure 2: Histogram, Gaussian and Student t Probability Density Function of Daily Returns

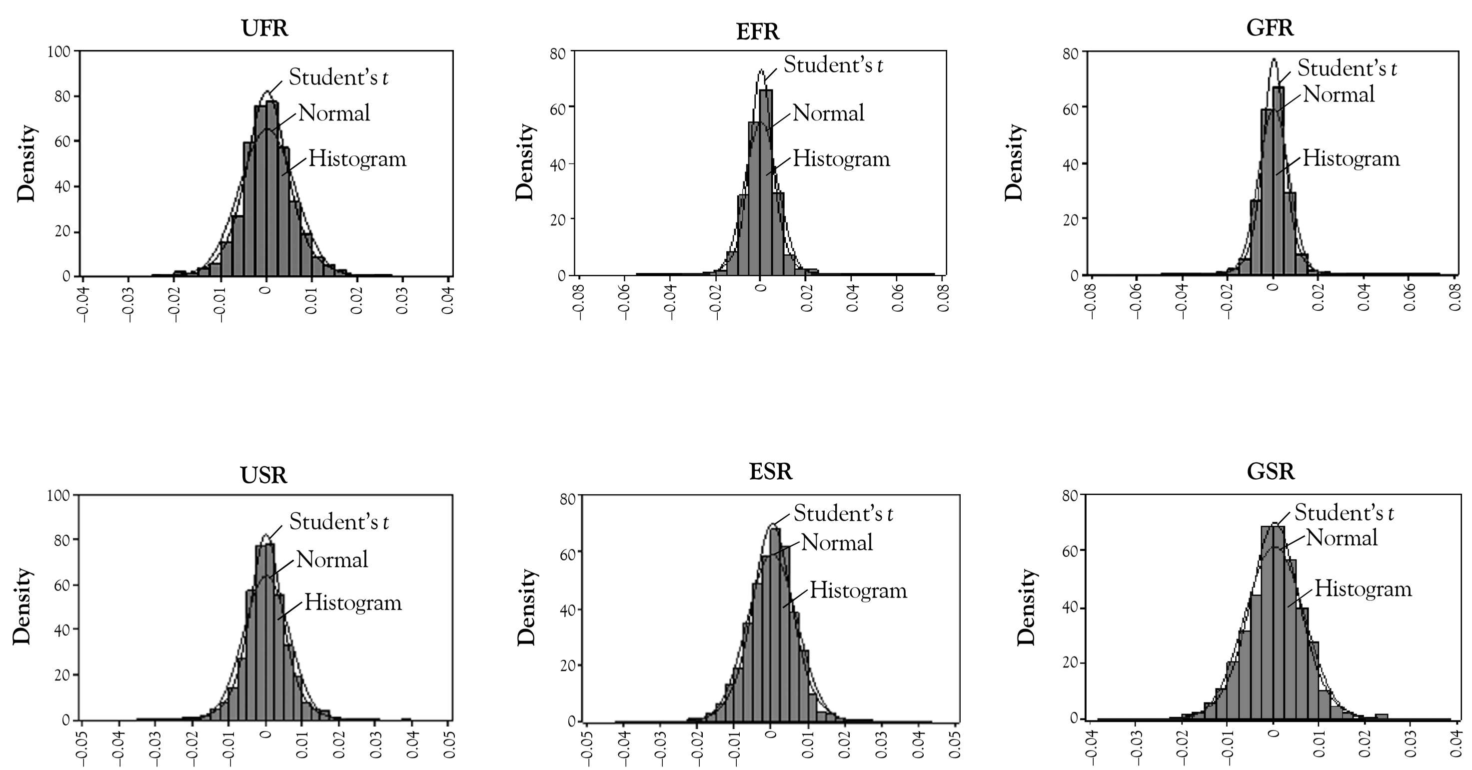

Figure 3: QQ Plots Versus Normal Distribution

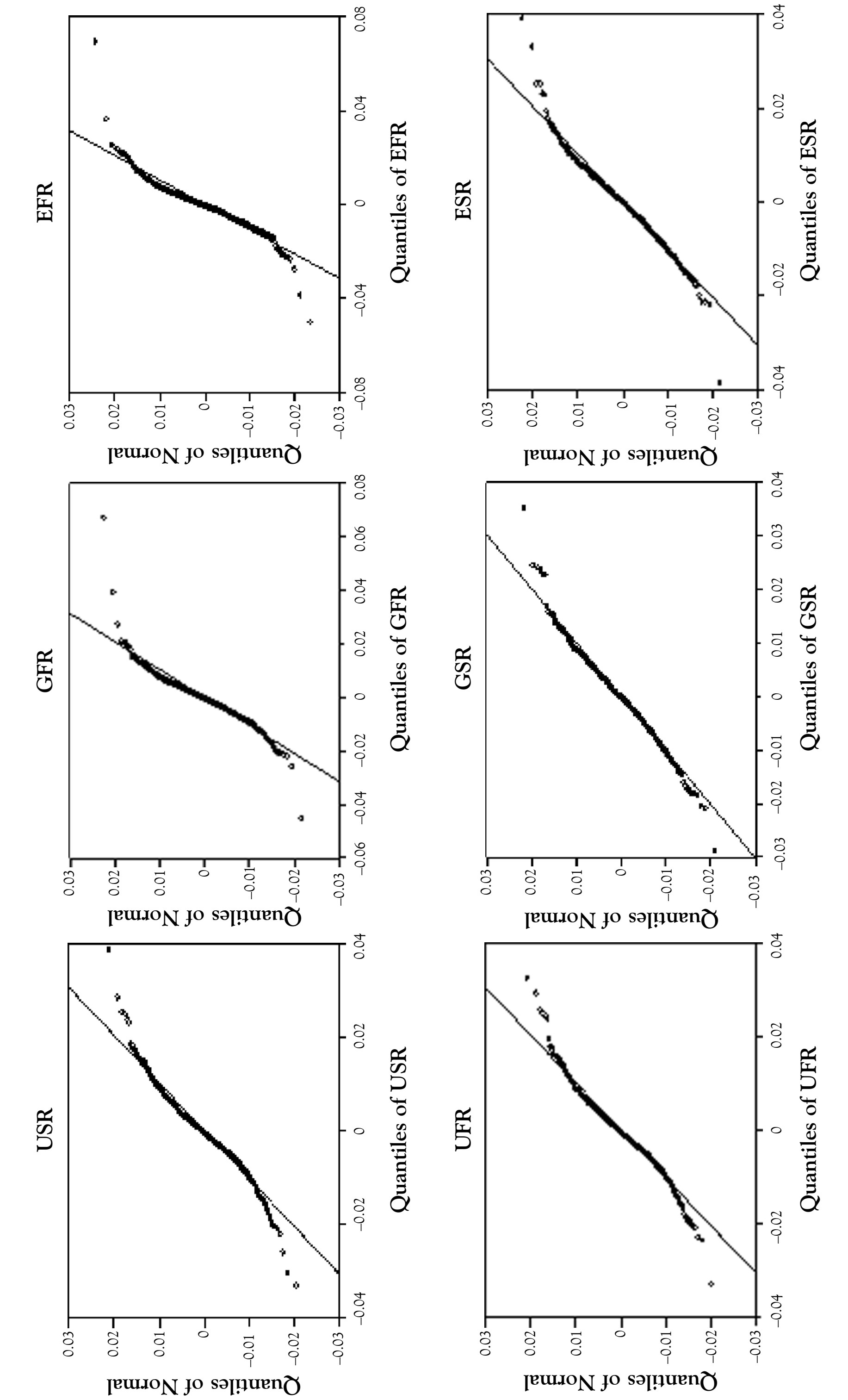

Table 2: Value-at-Risk Forecast Estimates (in %)														
		Student *t* Linear VaR			Historical Simulation			Monte Carlo Simulation			EWMA			
		99%	95%	90%	99%	95%	90%	99%	95%	90%	99%	95%	90%	
INR-Euro	Spot	1.79	1	0.71	–1.23	–1.41	–1.61	–10.27	–7.63	–5.99	11.03	7.80	6.08	
	Futures	1.94	1.09	0.78	–1.55	–0.99	–0.78	–10.03	–7.44	–5.87	10.19	7.21	5.62	
INR-GBP	Spot	1.71	0.96	0.68	–1.65	–1.36	–0.94	–1.98	–1.46	–1.15	1.00	0.71	0.55	
	Futures	1.77	1.00	0.71	–1.65	–1.36	–0.94	–1.81	–1.33	–1.05	1.08	0.77	0.60	
INR-USD	Spot	1.65	0.93	0.66	–1.37	–0.81	–0.60	–5.65	–4.20	–3.30	0.98	0.69	0.54	
	Futures	1.62	0.91	0.65	–1.39	–0.74	–0.54	–5.66	–4.17	–3.29	0.96	0.68	0.53	

The total number of observations is split into two sample periods. The first 100 observations are in-the-sample. From 101st observation it is out-of-sample period. Since the length of the data is limited, small period is considered for in-the-sample. The limited number of observations is attributed to the late introduction of currency futures in the Indian derivative markets. The historical simulation VaR and EWMA VaR are performed using a one-day rolling window of 100 observations. Monte-Carlo VaR is performed using 1,000 simulations. Except in certain cases, VaR has high degree of correlation with confidence interval. As the confidence interval increases, the expected loss also increases under all VaR models considered for both currency spot and futures market. The Monte-Carlo VaR estimates are comparatively higher at all confidence intervals for all currency pairs. Further, INR-Euro pair reports significantly higher VaR estimate at all confidence intervals, followed by INR-USD and INR-GBP currency pair. The results of EWMA are almost equal to that of Monte-Carlo with respect to VaR estimates of all currency pairs.

Evaluation of Value-at-Risk Models

Table 3 provides the results of backtesting test statistics calculated to verify the accuracy of the VaR estimates. The χ^2 critical values for one and two degrees of freedom are given in Table 4 at 90%, 95% and 99% confidence intervals. The tests used for testing the accuracy of VaR estimates are: the unconditional coverage (LRuc) test, test of independence (LRind) and conditional coverage (LRcc) test. The unconditional coverage test tries to test the null hypothesis that the VaR model is accurate, i.e., the total number of exceedances is close to the expected number of exceedances. This test follows a χ^2 distribution with one degree of freedom. Test of independence is used to test the null hypothesis that exceedances or violations are independent or not serially correlated. Independence test is unable to detect the clustering in exceedances. This is because the test is based only on first-order Markov chain and in order to detect the type of clustering, the test has to be extended to a high-order Markov chain to allow more than first-order dependence (Alexander, 2010). The conditional coverage test is a combination of LRuc and LRind. The test statistic values of various backtesting methods are compared with the χ^2 critical values for acceptance or rejection of the null

Table 3: VaR Backtesting Results										
		Historical Simulation			Monte-Carlo Simulation			EWMA		
		99%	95%	90%	99%	95%	90%	99%	95%	90%
INR-Euro Spot	LRuc	0.16	31.78	88.88	0.00	43.02	127.67	77.02	83.11	60.71
	LRind	*0.00	*3.16	*2.86	*3.25	*2.84	2.84	*4.67	*1.55	3.56
	LRcc	×0.00	34.94	91.73	×3.25	45.87	130.51	81.69	84.67	64.27
INR-Euro Futures	LRuc	0.34	27.16	14.80	0.00	43.02	123.14	116.82	100.47	76.11
	LRind	*0.00	*1.25	2.82	*3.25	*2.84	*2.49	*0.55	*4.82	*1.86
	LRcc	×0.00	28.41	17.62	×3.25	45.87	125.63	117.37	105.29	77.97
INR-GBP Spot	LRuc	1.27	4.17	14.80	5.73	37.13	6.68	72.78	90.86	70.90
	LRind	*0.00	*1.25	2.82	*0.00	*0.00	3.04	*3.08	*0.36	*0.88
	LRcc	×0.00	×5.42	17.62	×0.00	×0.00	9.72	75.86	91.22	71.78
INR-GBP Futures	LRuc	!0.16	25.04	42.26	5.73	31.92	63.86	45.49	21.96	22.63
	LRind	*3.73	4.45	7.99	8.02	*1.64	*0.07	9.57	*2.63	*0.66
	LRcc	×3.89	29.49	50.25	13.76	33.56	63.93	55.05	24.59	23.28
INR-USD Spot	LRuc	5.16	2.37	*2.10	0.00	0.00	0.00	1.94	0.00	1.94
	LRind	*0.00	*0.00	–0.04	*0.00	*0.00	*0.00	*2.09	11.07	13.16
	LRcc	×0.00	×0.00	×–0.08	×0.00	×0.00	×0.00	×5.30	17.43	22.72
INR-USD Futures	LRuc	1.64	2.37	18.84	0.00	0.00	0.00	0.75	1.05	4.39
	LRind	*0.00	*2.29	–3.65	*0.00	*0.00	*0.00	*0.00	8.76	9.17
	LRcc	×0.00	×2.29	–68.70	×0.00	×0.00	×0.00	×0.75	9.82	13.57

Note: The shaded cells indicate that the VaR estimates are accurate and not rejected by any backtesting method; * indicates VaR estimates are accurate and not rejected by the LRind test; ! and × indicate the acceptance of accurate VaR estimates by LRuc and LRcc tests, respectively.

Table 4: χ^2 Critical Values			
df	1%	5%	10%
1	6.63	3.84	2.71
2	9.21	5.99	4.61

hypothesis. The results of the parametric VaR are not shown as it showed maximum violation and could not pass the backtesting accuracy test at all confidence intervals. EWMA VaR performed well in all the backtesting criteria only with respect to INR-USD currency pair at 99% confidence interval. This indicates that the total number of exceedances is close to or less than the expected number and also exceedances are not serially correlated. Historical simulation VaR and Monte-Carlo simulation VaR perform well at 99% confidence interval for all backtesting methods and all currency pairs spot and future markets. It is evident from Table 3 that it is only for INR-USD currency pair spot and future series that the prediction ability of the Monte-Carlo simulation model holds good at all confidence intervals. The violation test statistics are almost less than the χ^2 critical value at all significance levels. Historical simulation and EWMA model test statistics results are almost the same. Except for a few instances, one common observation that is evident from Table 3 is that, all currency pairs of the series are not rejected for the test of independence. The reason may be that there are few exceedances during tranquil markets when volatility is low, and too many when volatility is high (Alexander, 2010). Even if a few exceedances seem to be appearing to form clusters, the exceedances may be separated by one or two days of good returns.

Conclusion

In the paper, an attempt was made to study the comparative predictive ability of various VaR approaches. Evaluation results indicate that the VaR models pass the backtesting criteria at higher confidence interval. On the whole, Monte-Carlo simulation VaR model yields superior results for all the currency pair series at 99% confidence interval. While estimating the expected loss using VaR models, it is very necessary for the models to capture the extreme events in the values of the financial time series. This is because financial time series are characterized by fat-tailed distributions and only a better model would be able to capture the extreme movements in the time series data. At the same time, sample size of the time series data also determines the superiority of the model. A small in-the-sample-based VaR fails in forecasting or backtesting the out-of-sample observations. Further, the probable reason for not rejecting the test of independence might be that the introduction of currency futures has reduced volatility in the spot currency market. This is evident from the above analysis as the expected loss in spot markets is less than in futures market. ❖

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