Is USD-INR really a volatile currency pair?

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Introduction

- The FX market is the largest financial market in the world.
- Forex volatility is always an important concern for financial market agents, especially for exporters, importers, investors, fund managers, bankers and central banks.
- The growing sentiments of global risk aversion, poor macroeconomic performance, and central banks' macroeconomic policies have all led to high volatility in currencies in recent years.
- EM currencies are more volatile in nature due to their small share in global trade, low liquidity in financial markets and relatively weaker macroeconomic conditions.

Introduction

- The USD-INR is considered by most traders, investment bankers, news agencies and financial market reporters to be highly volatile.

- We are interested in examining whether this observation is true in reality.

- Three currency pairs (USD-INR, EUR-INR, GBP-INR) are taken for the study.

- Most estimation procedures tend to use only daily closing prices. In contrast, this study looks at the problem of the estimation of volatility by using extreme values (high, low).

Literature

- ***Shiller (1979)-*** short-term holdings yields on long-term bonds are excessively volatile.

- ***Shiller (1981)-*** the efficient markets model is not reflected in real observed data.

- **Leroy and Porter (1981)-** high volatility in aggregated and disaggregated US stock price data.

- **Kleidon (1981)-** investors placed high importance on short-run factors leading to an overreaction in prices.

- **Shiller (1985)** - Stock price movements can not be justified by only dividends over the period

Literature

- ***De Bondt and Thaler (1985)-*** enough evidence to support the overreaction hypothesis in US stock.

- ***De Long & Grossman (1993)-*** excess volatility in British Stocks.

- ***Cuthbertson and Hyde (2002)-*** excess volatility in the French and German stock markets.

- ***Heaney (2004)-*** stock market prices were more sensitive to dividend variation than predicted in Australian stock data

Motivation

- Most of the literature are based on stock prices or stock indices or bonds.
- There is sufficient scope to contribute further knowledge about excess volatility in FX markets.
- There is an apparent shortage of research on emerging market currencies on the same lines.
- This paper attempts to fill this gap by studying excess volatility of Indian rupee, which is a major emerging currency.

Data Description

- The dataset consists of daily prices, viz., Open, High, Low, and Close (OHLC) prices of three currency pairs USD-INR, EUR-INR and GBP-INR

- The sample period taken is 01st January 2009 to 30th June 2015. All the data have been collected from the Bloomberg database.

Methodology

- We replicate extreme value estimator proposed by ***Rogers and Satchell (1991)*** to estimate the volatility parameter and use VRatio proposed by ***Maheswaran, Balasubramanian & Yoonus (2011)***.

- RS is an estimator for the unconditional variance and is also unbiased for any value of the drift.

- The RS estimator is unbiased in the context of Brownian motion i.e., if the intraday price series follows a Brownian motion.

- In order to apply the Brownian motion model, the data are put through the transformation described next.

Methodology

- $\mathrm{p_t}$ denotes price of the asset between open and close times, and trading start and close times are denoted by t = 0 and 1 respectively.

- Let $x_{n,t}$ represents the intra-day (log) price on day n when normalized by the opening price as,

$$x_{n,t} = \log(\mathrm{p_t} \text{ on day n}) - \log(\text{Open price on day n}) \quad \text{for } 0 \le t \le 1,$$

- Normalized price $x_{n,t}$, we can define the normalized maximum and minimum prices

Methodology

- Then, we can rewrite normalized log prices for High (maximum), Low (Minimum) and Last (Terminal) values as defined below.

$$\mathrm{b}_{\mathrm{n},1} = \log(\text{High price on day n}) - \log(\text{Open price on day n})$$
$$\mathrm{c}_{\mathrm{n},1} = \log(\text{Low price on day n}) - \log(\text{Open price on day n})$$
$$\mathrm{x}_{\mathrm{n},1} = \log(\text{Close price on day n}) - \log(\text{Open price on day n})$$

- $x_{n,t}$ process, as defined earlier, is a Brownian motion with drift μ and variance σ^2.

- Sample of observations (x_{n} b_{n}, c_{n}) is calculated from Open High Low Close (OHLC) data.

Methodology

- In order to determine the RS estimator (*Rogers and Satchell, 1991*)

Let $u_n = 2b_n - x_n$ and $v_n = 2c_n - x_n$,

We define the extreme values ux and vx as:

$ux = \frac{1}{2}({u_n}^2 - {x_n}^2)$ and $vx = \frac{1}{2}({v_n}^2 - {x_n}^2)$

Now, If we take the average of these two extreme values and define it as $uxvx$ then,

$uxvx = \frac{1}{2}(ux + vx)$

Methodology

- Hence, from the daily OHLC prices we can calculate the daily $uxvx$ prices.

- If we then take an average of daily $uxvx$ prices over the entire sample time period, we will get the extreme value estimator of variance, viz., the RS estimator

$$\mathrm{RS} = \frac{1}{N}\sum_{n=1}^{N} uxvx$$

- The usual variance of the time series is defined as

$$\mathrm{Var}(x) = \frac{1}{N-1}\sum_{n=1}^{N}(x_n - \hat{\mu})^2$$

Methodology

- Under the Brownian motion assumption, the RS estimator is uncorrelated with the usual sample variance (***Maheswaran et al., 2011***).

- The VRatio is the ratio of the RS estimator and the sample variance.

$$\text{VRatio} = \text{RS} / \text{Var}(x)$$

Simulation

- Un-biasedness property of extreme value estimator depends on the extent of Brownian motion approximation of the sample data. Using, multiple-days' horizon, it may be possible to obtain better approximation of the Brownian motion.

- We undertake a simulation study to investigate how this VRatio changes over a multiple-days horizon (to check if k-Days VRatio converges to unity).

- Specifically, it is to investigate whether the values observed in the currency data show any sign of excess volatility

Simulation

- We take days in our sample period as T = 1, 2, 3, ……, N and time windows as k = 1, 2, 3, ……, 20.

- From the OHLC data, we construct k-Days OHLC for each k

- Given T = 1, 2, 3, …., N and that k = 1, 2, 3, ……, 20, we can create our sample in the following way:

  Open = Open (T)

  High = Max (High (T: T+k-1))

  Low = Min (Low (T: T+k-1))

  Close = Close (T+k-1)

Simulation

- For all k = 1, 2, 3, ……, 20 we get OHLC data i.e. for each currency pair we will have 20 new sets of OHLC data.

- From each sample, we construct normalized extreme values (x_n, b_n, c_n), i.e., maximum, minimum and terminal values as defined earlier.

- We use this (x_n, b_n, c_n) to calculate the RS estimator, i.e., mean ($uxvx$).

- Then for each k = 1, 2, ….,20 we estimate

VRatio= RS/Var(x)

Simulation

- Now we consider 1000 bootstrap replications of the random sample with replacement, i.e., we create 1000 new samples for each actual sample.

- Here, we generate 1000 new bootstrap samples of (x_n, b_n, c_n) for a given k.

- From each bootstrap sample, we will determine the RS estimator and Var(x).

- Then estimate VRatio= RS/Var(x)

Simulation

- The same process is done for all 1000 new bootstrap samples and we finally take the average mean of all VRatios = Boot Mean, and the standard error of Boot VRatios = Boot σ
- We run the same simulation process for each k to generate 20 separate Boot means and Boot σ's to gain multiple-days' time window results.
- The same process is repeated for all the three currency pairs.

Empirical Findings

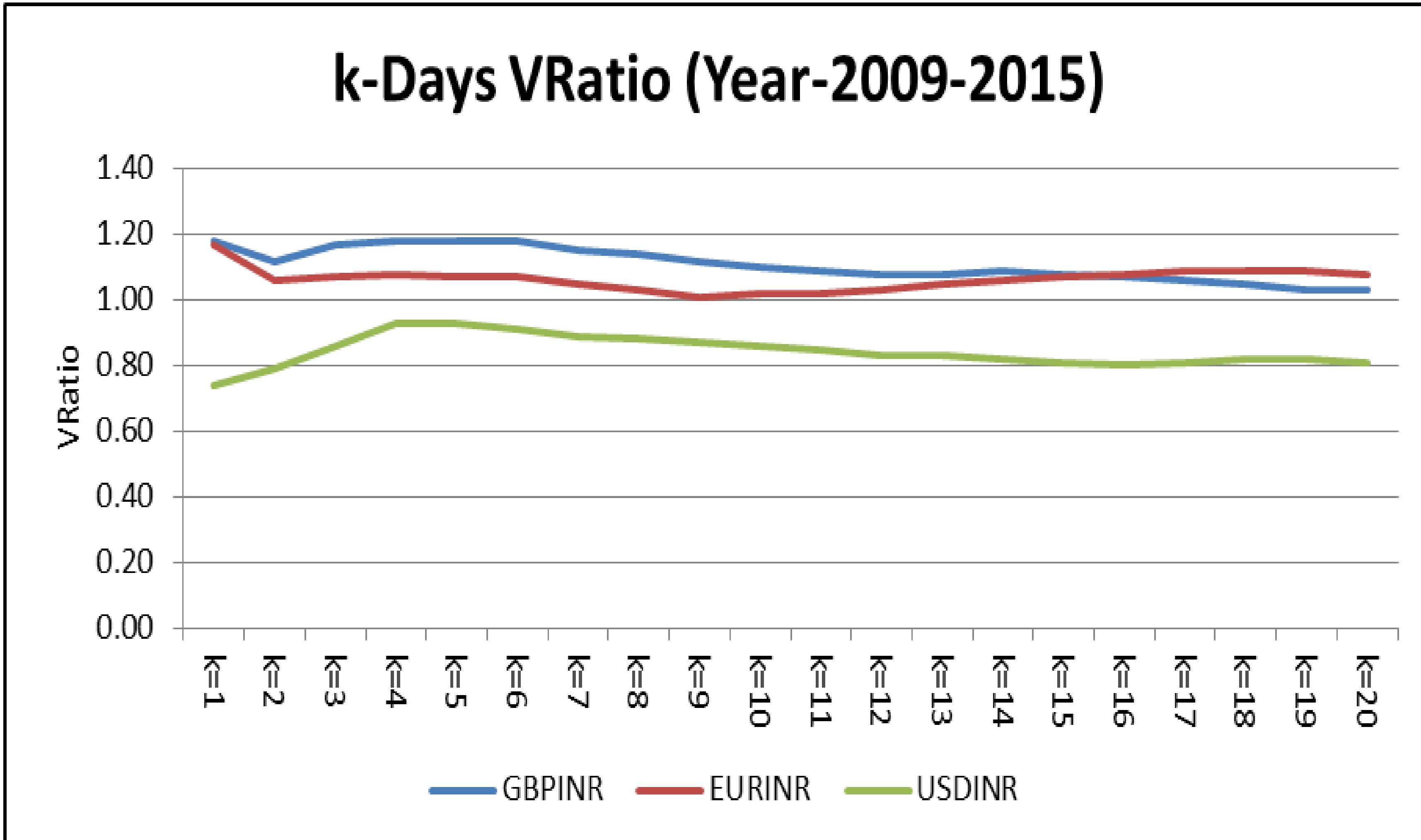
USDINR		GBPINR		EURINR	
VRatio	σ	VRatio	σ	VRatio	σ
0.74	0.04	1.19	0.06	1.18	0.07

- If VRatio > 1, then the extreme value estimator suffers from an upward bias relative to the ‘usual’ estimator Var(x), i.e., there is excess volatility in the market.

- This empirical finding that VRatio > 1 for EUR-INR and GBP-INR is could be because of negative correlation among intra-day price changes and existence of path dependency in price movements.

- USD-INR doesn’t show the same result.

Empirical Findings



Empirical Findings

	GBPINR			EURINR			USDINR		
k-Days	Actual VRatio	Boot Mean	Boot SE	Actual VRatio	Boot Mean	Boot SE	Actual VRatio	Boot Mean	Boot SE
k=1	1.18	1.19	0.06	1.17	1.18	0.07	0.74	0.74	0.04
k=2	1.12	1.12	0.06	1.06	1.07	0.06	0.79	0.79	0.05
k=3	1.17	1.17	0.06	1.07	1.07	0.05	0.86	0.87	0.06
k=4	1.18	1.18	0.05	1.08	1.08	0.05	0.93	0.94	0.05
k=5	1.18	1.18	0.05	1.07	1.08	0.05	0.93	0.93	0.05
k=6	1.18	1.18	0.05	1.07	1.08	0.05	0.91	0.92	0.05
k=7	1.15	1.15	0.05	1.05	1.05	0.05	0.89	0.90	0.04
k=8	1.14	1.15	0.05	1.03	1.03	0.05	0.88	0.88	0.05
k=9	1.12	1.12	0.06	1.01	1.00	0.05	0.87	0.87	0.04
k=10	1.10	1.10	0.06	1.02	1.02	0.05	0.86	0.86	0.04
k=11	1.09	1.09	0.05	1.02	1.03	0.05	0.85	0.85	0.04
k=12	1.08	1.08	0.05	1.03	1.04	0.05	0.83	0.84	0.04
k=13	1.08	1.09	0.05	1.05	1.05	0.05	0.83	0.83	0.04
k=14	1.09	1.09	0.05	1.06	1.06	0.05	0.82	0.82	0.04
k=15	1.08	1.09	0.05	1.07	1.07	0.05	0.81	0.81	0.04
k=16	1.07	1.07	0.05	1.08	1.08	0.05	0.80	0.80	0.04
k=17	1.06	1.06	0.05	1.09	1.09	0.05	0.81	0.81	0.04
k=18	1.05	1.05	0.05	1.09	1.09	0.05	0.82	0.82	0.04
k=19	1.03	1.04	0.05	1.09	1.09	0.05	0.82	0.82	0.04
k=20	1.03	1.03	0.05	1.08	1.08	0.05	0.81	0.82	0.04

Empirical Findings

- We find excess volatility in EUR-INR and GBP-INR currency pairs but unexpectedly, not in USD-INR.

- We have constructed multiple-day time windows (k-Days) to check if k-Days VRatio converges to unity. VRatio is already more than unity for EUR-INR and GBP-INR for a one-day time window, decreases with respect to the length of the time window and converges to unity for both.

- In the case of the USD-INR, which is lesser than unity for a one-day time window, the VRatio converges to around 0.80 when we consider a multiple-days' time window.

- High low volatility estimates (RS estimator) is just 80% of the open to close volatility.

Empirical Findings

- Hence, it makes us wonder whether in fact the USD-INR currency pair is excessively volatile because, we don't find sufficient evidence to justify the hypothesis that the USD-INR currency pair is excessively volatile.

Possible Reason ?

Possible Reason

- The possible reason could be that during high volatility in rupee, the RBI actively participates in the FX markets and ensures that the rupee reaches market -determined values vis-à-vis the US dollar steadily and without any sharp moves.

- **Prakash, A (2012**) observed that during high exchange rate volatility, RBI has intervened in the market and has taken other monetary and administrative measures to meet the threats to financial stability.

Conclusion

- We use extreme value volatility estimators to study currency markets specially focusing on India.
- We find excess volatility in EUR-INR and GBP-INR currency pairs but we don’t see evidence of it in USD-INR.
- We believe RBI is probably doing a great job in managing USD-INR volatility but not in case of EUR-INR and GBP-INR.

Further Research

- We plan to extend our work on other important asset classes.
- Currently, we are working on precious metals (Gold and silver) and stock indices of EM economies to see how their prices behave.

Thank You