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EXCHANGE RATE VOLATILITY IN INDIAN MARKETS USING GARCH MODELS

Dr. Jagannayaki K, Dr. Sreekanth Yerramilli, Vara Lakshmi Thavva and Nunna Suresh

[1] Professor, MBA Dept., Institute of Aeronautical Engineering, Dundigal, Hyderabad, Telangana, India-500043, kjagannayaki@gmail.com Dundigal, Hyderabad, Telangana, India-500043 ORCID: 0000-0002-0531-4434

[2] Dept. of Management Sciences , SunStone-MRU University drsreekanthyerramilli@gmail.com

[3] Professor, MBA Dept., Institute of Aeronautical Engineering., Dundigal, Hyderabad, Telangana, India-500043, mvaralu2011@gmail.com, ORCID: 0000-0002-7456-1922, ORCID: 0000-0002-6493-7463

[4] Assistant Professor, MBA Dept., Institute of Aeronautical Engineering, Dundigal, Hyderabad, Telangana, India-500043, nunnasuresh.81@gmail.com

Abstract:

The present study focuses on the time series behaviour of select currencies using GARCH Models. Monthly returns of currency prices exhibit aggressiveness and high degree of interdependence. In particular, generalized autoregressive conditional heteroscedastic GARCH (1, 1) processes fit to data very satisfactorily. Various out-of-sample forecasts of monthly return variances are generated and compared statistically. Forecasts based on the GARCH model are found to be superior. The common assumptions of this model is interdependence and linearity. This paper aims to model the volatility of INR exchange rates against USD for the period from January 2000 to 5 January 2023 using the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models. Both symmetric and asymmetric models have been applied to measure factors that are related to the exchange rate returns such as leverage effect and volatility clustering. Based on the results, the static forecast of GJR-GARCH (1, 1) is the best model in predicting the future pattern for both INR and USD.

Keywords: Exchange Rates, Aggressiveness, interdependency, linearity, leverage effect,

volatility clustering.

Introduction:

For the last few days, we have been heeding that the Indian Rupee (INR) is depreciating heavily hitting an all-time low of 82 to the US dollar. The depreciating rupee influences the domestic economy as well as the stock market. For a common man, the domestic currency is a standard medium of money to exchange goods & services, but the exact definition is indefinable due to the fluctuation in the value of the currency.

Investors need accurate forecasts about future values of exchange rates. For this, exchange rate volatility is a useful measure of uncertainty about the economic environment of a country. This study analyses univariate, nonlinear time series to the daily (INR/USD) exchange rate data from January 1, 2000 to January 5, 2023 to examine the behavior of exchange rate in India. ARCH and GARCH models used to detect the symmetry effect in exchange rate data. Also, the paper employs exponential GARCH (EGARCH) model to capture the asymmetry in volatility clustering and to identify the leverage effect in exchange rate. The study discloses that exchange rate series exhibits the empirical regularities such as clustering volatility, non-stationarity, non-normality and serial correlation that justify the application of the ARCH methodology. This paper reveals the results about the exchange rate behaviour influenced by previous historical exchange rates. This also implies that previous day's volatility in exchange rate can affect current volatility of exchange rate. In addition, the estimate for asymmetric volatility suggests that positive shocks imply a higher next period conditional variance than negative shocks of the same sign. The main purpose of the study is to create awareness about exchange rate volatility may have its impact on transaction cost and international trade. It reveals how exchange rate volatility (exchange-rate risk) may increase transaction costs and reduce the gains to international trade, exchange rate volatility estimation and forecasting is important for asset pricing and risk management.

Purpose:

US Dollars is considered as the benchmark for global transactions and therefore it has a direct impact upon the strength of the Indian Rupee. India being US' ninth largest goods trading partner, the two countries enjoy strong collaborations in precious metals and stone, mineral fuels and pharmaceuticals which makes the USD/INR pair an exciting one for the traders looking to earn profit for long term and also for short term opportunities. To capture the symmetry/asymmetry effect in exchange rate data, the paper applies both ARCH and GARCH models. Prediction of exchange rate behaviour done by past historical exchange rates. Various forms of statistical models have been evolved to capture the volatility effect. These models are often applied for estimating the degree of the exchange rate instability.

Objectives:

1. To examine the interdependency and linearity of select currency exchange rates

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2. To assess the trend patterns of time series of select currency behaviour
3. To measure the characteristics of exchange volatility
4. To identify the reasons for INR depreciation

Methodology:

The present study based on empirical evidences of select currencies. This study targets to determine the US Dollar against IND Rupee exchange rate behaviour pattern using GARCH models and to make a comparison between them. USD and INR have been chosen as the two currencies, which are widely used, and trusted currencies in the business world and both are among the world's currencies that are accepted for most international transactions. For that purpose, the paper applies part of GARCH family models using daily observations quoted from EXINUS from January 2000 until January 2023. So, the research hypothesis is that USD versus INR exchange rate volatilities can be determined using GARCH models. The volatility models applied are ARCH, GARCH, Weighted ARCH LM Tests, Weighted Ljung-Box Test, Sign Bias Test and PGARCH. In the end, the paper tests the best model for future forecasting of time series volatility.

Result Analysis:

```
*---------------------------------*
*        SGARCH Model Fit         *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model     : sGARCH(1,1)
Mean Model      : ARFIMA(1,0,0)
Distribution : std

Optimal Parameters
------------------------------------
      Estimate   Std. Error t value    Pr(>|t|) mu      0.000105
0.000933  0.11234   0.910551 ar1     0.298889    0.060222
4.96312   0.000001 omega   0.000004    0.000007  0.50607
```

P-ISSN: 2204-1990; E-ISSN: 1323-6903

0.612809 alpha1 0.133723 0.046708 2.86294 0.004197
beta1 0.865277 0.055027 15.72457 0.000000 shape
4.030127 0.899651 4.47966 0.000007

Log Likelihood: 809.1403

Information Criteria

Akaike -5.7367
Bayes -5.6588
Shibata -5.7376
Hannan-Quinn -5.7055

Weighted Ljung-Box Test on Standardized Residuals
----
statistic p-value Lag[1] 0.05707 0.8112
Lag[2*(p+q)+(p+q)-1][2] 0.12462 0.9998
Lag[4*(p+q)+(p+q)-1][5] 0.81975 0.9701 d.o.f=1
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
----
statistic p-value Lag[1] 0.6597 0.4167
Lag[2*(p+q)+(p+q)-1][5] 2.8499 0.4351
Lag[4*(p+q)+(p+q)-1][9] 4.3203 0.5354

d.o.f=2

Weighted ARCH LM Tests

	Statistic	Shape	Scale	P-Value
ARCH Lag[3]	1.682	0.500	2.000	0.1947
ARCH Lag[5]	2.898	1.440	1.667	0.3049
ARCH Lag[7]	3.203	2.315	1.543	0.4760

Nyblom stability test

P-ISSN: 2204-1990; E-ISSN: 1323-6903

Joint Statistic: 4.4558
Individual Statistics:
mu 0.3534 ar1 0.6063
omega 0.7169 alpha1 0.1626
beta1 0.2775 shape 0.8328

Asymptotic Critical Values (10% 5% 1%)
Joint Statistic: 1.49 1.68 2.12
Individual Statistic: 0.35 0.47 0.75

Sign Bias Test
------------------------------------ t-value
prob sig

Sign Bias 0.07721 0.9385
Negative Sign Bias 0.33749 0.7360
Positive Sign Bias 0.27938 0.7802
Joint Effect 0.51279 0.9161

Adjusted Pearson Goodness-of-Fit Test: --------
---------------------------- group statistic p-
value(g-1) 1 20 16.14 0.6477
2 30 32.86 0.2835
3 40 40.00 0.4256
4 50 45.71 0.6071

Elapsed time: 1.07667

----
* EGARCH Model Fit *

Conditional Variance Dynamics

GARCH Model : eGARCH(1,1)
Mean Model : ARFIMA(1,0,0)
Distribution : std

Optimal Parameters
------------------------------------ Estimate Std. Error t value Pr(>|t|) mu -0.000463 0.000981 -0.47167 0.637161 ar1 0.320482 0.057222 5.60073 0.000000 omega 0.017630 0.006893 2.55783 0.010533 alpha1 -0.109573 0.070517 -1.55384 0.120222 beta1 1.000000 0.001277 783.18049 0.000000 gamma1 0.265883 0.059568 4.46353 0.000008 shape 2.932058 0.839907 3.49093 0.000481

Robust Standard Errors:
Estimate Std. Error t value Pr(>|t|) mu -0.000463 0.002001 -0.23137 0.817026 ar1 0.320482 0.078843 4.06483 0.000048 omega 0.017630 0.019883 0.88669 0.375244 alpha1 -0.109573 0.117235 -0.93464 0.349973 beta1 1.000000 0.001761 567.91980 0.000000 gamma1 0.265883 0.081818 3.24970 0.001155 shape 2.932058 1.249533 2.34652 0.018950

LogLikelihood : 811.7415

Information Criteria

Akaike -5.7482
Bayes -5.6573
Shibata -5.7494
Hannan-Quinn -5.7117

Weighted Ljung-Box Test on Standardized Residuals ---------
--------------------------- statistic p-value Lag[1]
0.08744 0.7675
Lag[2*(p+q)+(p+q)-1][2] 0.25162 0.9971
Lag[4*(p+q)+(p+q)-1][5] 0.89711 0.9610 d.o.f=1
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
----
statistic p-value Lag[1] 3.903 0.04819

Lag[2*(p+q)+(p+q)-1][5]   5.915 0.09416
Lag[4*(p+q)+(p+q)-1][9]   7.775 0.14249 d.o.f=2

Weighted ARCH LM Tests

Statistic Shape Scale P-Value
ARCH Lag[3]   2.236 0.500 2.000 0.1349
ARCH Lag[5]   3.371 1.440 1.667 0.2404
ARCH Lag[7]   3.871 2.315 1.543 0.3656

Nyblom stability test

Joint Statistic: 2.7808 Individual Statistics:
mu   0.3750 ar1
0.4591 omega
0.1080 alpha1
0.6863 beta1 0.1274
gamma1 0.1453
shape 0.3505

Asymptotic Critical Values (10% 5% 1%) Joint
Statistic: 1.69 1.9 2.35 Individual Statistic: 0.35
0.47 0.75

Sign Bias Test
------------------------------------   t-value
prob sig Sign Bias   0.09653 0.9232
Negative Sign Bias 0.14077 0.8882
Positive Sign Bias 0.14498 0.8848
Joint Effect   0.06069 0.9961

Adjusted Pearson Goodness-of-Fit Test: --------
--------------------------- group statistic   p-
value(g-1) 1   20   20.86   0.3447
2   30   32.21   0.3105
3   40   31.43   0.8004
4   50   47.86   0.5195
Elapsed time: 1.34223

P-ISSN: 2204-1990; E-ISSN: 1323-6903

Interpretation:

1. The table of the estimated optimal parameters shows the significance of the estimated pa rameters. It shows that the constant parameter omega1 (parameter w1 in the model settin g) tends to be non-significant, meaning that the constant parameter seems to be not usefu l in this model setting.
2. The information criteria displays the Akaike (AIC), Bayes (BIC), Hannan-Quinn and Shi bata criteria for the model estimation. The lower these values, the better the model is in t erms of fitting.
3. The next table presents the Ljung-Box test for testing the serial correlation of the error terms. The null hypothesis is that there is no serial correlation of the error terms. The decision rule is simple. Basically, if the p-value is lower than 5%, the null hypothesis is rejected. As we can see that the p-value is higher than 5%, meaning that there is not enough evidence to reject the null hypothesis. Then there is no serial correlation of the error term.
4. Adjusted Pearson Goodness of Fit, concerning the goodness of fit of the error. Indeed, it is useful to check if the error term follows the normal distribution. The null hypothesis is that the conditional error term follows a normal distribution. If the p-value is lower than 5%, the null hypothesis is rejected. As we can see, the normal distribution is by far rejected (as the p-value is close to zero).
5. The Weighted ARCH LM test shows that the ARCH model is globally significant as its global p-value is close to zero.

6. For the goodness of fit of the residual to the considered skewed student distribution, we can see that the p-value is greater than 5%, meaning that there is not enough evidence to reject the fact that the residuals fit well that distribution.

7. This setting displays a non-significant drift for the volatility and a non-significant gamma for the GJR-GARCH.

8. The recent INR depreciation has surprised the market leading to 10% depreciation in a year, which is double than the normal rate of 4 to 5 per cent annually, raising questions about the strength of the Indian economy.

Inference: The analysis of the exchange rate volatility in Indian markets using SGARCH and EGARCH models reveals the following key findings:

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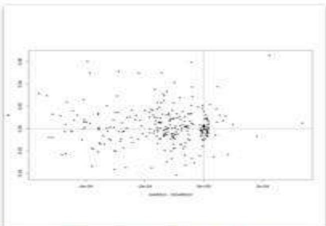
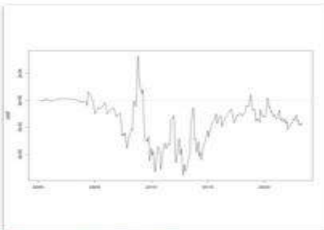
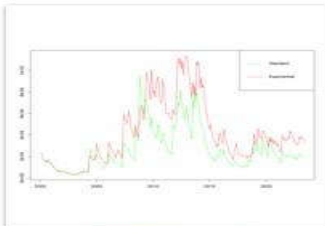
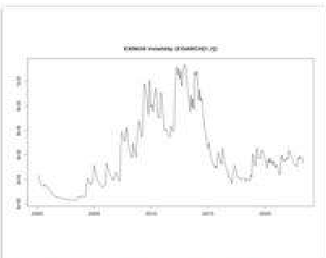
- Both models, SGARCH and EGARCH, provide satisfactory fits to the data, indicating their ability to capture the volatility dynamics of the Indian Rupee (INR) exchange rates against the US Dollar (USD).
- The estimated parameters of the models shed light on the mean, autoregressive terms, omega, alpha1, beta1, gamma1, and shape, which play a crucial role in modeling the volatility.
- Both models show no significant serial correlation in the standardized residuals, suggesting that the models effectively capture the temporal dependence in the volatility patterns.
- While the weighted ARCH LM tests do not indicate significant autoregressive conditional heteroscedasticity, evidence of serial correlation is found in the squared residuals of the EGARCH model at certain lag orders.
- The Nyblom stability tests demonstrate parameter stability in both models, indicating that the estimated parameters remain consistent over time.
- The sign bias tests reveal no systematic bias in the residuals of either model, indicating that the models adequately capture the directional movement of the exchange rates.
- The adjusted Pearson goodness-of-fit tests indicate reasonably good fit between the models and the data, further supporting the models' effectiveness in modeling the exchange rate volatility.

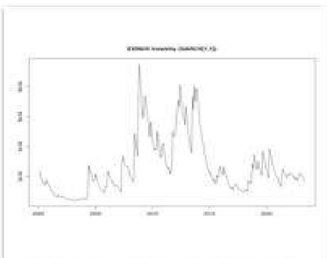
Graphical Representation of Volatility:

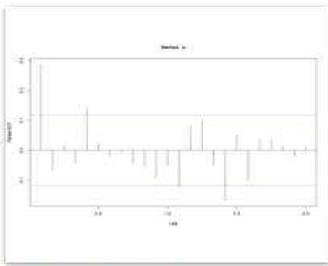

Plot OF GARCH AND EGARCH


Plot OF VOLDEF


Plot OF COMPARISSION


Plot OF EXINUS EGARCH


Plot OF EXINUS VOLATILITY


Plot OF SERIES E

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The results of the other plots showing the performance of the model similar to the one presented in the table results. The graphs show that the residuals are not that perfectly aligned with the straight line, meaning that the residuals do not follow the normal distribution. This result can also be confirmed by the plot of the residuals kernel and the normal distribution.

US Dollar Performance

	Current	1 Month	6 Month	1 Year	3 Year	5 Year
USD/INR	81	2	7	10	5	5
USD/JPY	145	4	18	29	10	5
USD/CNY	7	3	12	10	0	1
USD/EUR	1	3	13	19	4	4
USD/GBP	1	6	19	21	4	4

Source: Geojit Financial Services • Get the data • Created with Datawrapper

India Rupee Performance

	Current	1 Month	6 Months	1 Year	3 Year	5 Year
JPY/INR	0.56	-2.00	-10.00	-15.00	-5.00	-1.00
CNY/INR	11.50	0.00	-4.00	-0.40	5.00	3.00
EUR/INR	79.50	0.00	-5.00	-8.00	1.00	1.00
GBP/INR	90.00	-3.00	-10.00	-10.00	1.00	1.00

Source: Bloomberg| Geojit Financial Services. • Get the data • Created with Datawrapper

This also means that INR has actually appreciated to other currencies like 10% to pound, 8% to Euro, 15% to Yen and 0.4% to Yuan, at the same time. As a result, we should not be concerned about the current volatility because it is due to global economic & geopolitical uncertainties.

India is in a safe position and its currency will rebound firmly as this patch of volatility is dispersed.

The ongoing volatility is expected to persist in the short term as the global economy slows in 20222023. The same will continue to affect the currency market due to plausible shifts of crosscurrencies to USD.

Today, the USD is appreciating against the rest of the world currencies despite fundamental weakness in its own domestic economy. This is due to the fact that the US economy consistently remains the biggest and most powerful economy, with the benefit of serving as the reserve currency for global commerce & investment. Thus, USD held to be the world's haven currency. A reversal will be triggered when the hazardous factors are well factored in the equity market.

This can happen as early as the end of 2022 or delayed to 2023, depending on the firm improvement in geo-political risk, hyperinflation, and global economic growth.

Why Is USD Becoming Stronger Than INR?

The reasons included:

1. Global tantrums and domestic factors such as rising inflation.
2. Dollar strengthened amid Russia-Ukraine conflict, global inflation concerns led surge in US Bond Yields, and the result is an appreciating Dollar.
3. Supply chain disruptions and food inflation have added up to the above reasons. RussiaUkraine war seems to have no solution and there is a slowdown in world's three largest economies i.e. US, China and Europe. Though Indian currency looks weaker, but there is an expectation that Indian economy will perform much better in the near future in the second half of the year 2022.
4. In the past few weeks, Corporate Dollar Demand, foreign fund outflows, risk averse sentiments and broad based strength in the dollar are the major factors that contributed to push the rupee towards lower side.
5. Also rise in inflation has put a high pressure on the Reserve Bank of India to hike interest rates. But in the near future the spot USD/INR seems to be bullish momentum oscillators and indicators.

Conclusion:

The ongoing global uncertainties have led to a risk-off policy by global investors. This leads to selling by foreign investors, which inherently increases demand for USD and supply of other currencies, leading to depreciation. The sustainability and relative value of a currency fluctuates due to several factors such as change in demand & supply of goods & services, change in the cost of the economy, rise & cut of interest rates, fiscal policy, govt's anti-inflationary measures, and inflation.

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