Exchange Rate Forecasting of INR/CNY: Econometric and Machine Learning Hybrid Approaches

TKSS ASHOK

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Abstract

This report investigates the forecasting of the INR/CNY exchange rate using econometric and machine learning methods. Starting with traditional time series approaches such as cointegration analysis, VECM, and VAR, we extend the framework to incorporate macro-financial exogenous drivers like Brent crude, COMEX copper, and the US Dollar Index (DXY). Finally, a hybrid VAR + XGBoost model is introduced to capture nonlinearities in the residuals. Results suggest that while traditional models capture the broad dynamics, hybrid methods provide superior short-term predictive accuracy.

1 Introduction

Exchange rates are influenced by macroeconomic fundamentals (interest rate differentials, CPI inflation, FX reserves) and global financial variables (commodity prices, USD strength). Forecasting them requires combining long-run equilibrium considerations with short-run volatility and nonlinear effects.

This project focuses on INR/CNY exchange rate prediction with:

- Monthly macroeconomic differentials (India vs. China).
- Daily financial drivers (Brent, Copper, DXY).
- Econometric models (VECM, VAR, ARIMAX).
- Hybrid machine learning corrections (VAR + XGBoost).

2 Theoretical Background

2.1 Stationarity and Unit Root Tests

For a series y_t, stationarity was tested using ADF and KPSS.

$$H_0^{ADF}: \text{ unit root exists}, \quad H_0^{KPSS}: \text{ stationarity holds}.$$

2.2 Cointegration and VECM

If y_t (INR/CNY) and fundamentals X_t are non-stationary but cointegrated, a Vector Error Correction Model is appropriate:

$$\Delta y_t = \alpha\beta' Z_{t-1} + \sum_{i=1}^{p} \Gamma_i \Delta Z_{t-i} + \varepsilon_t,$$

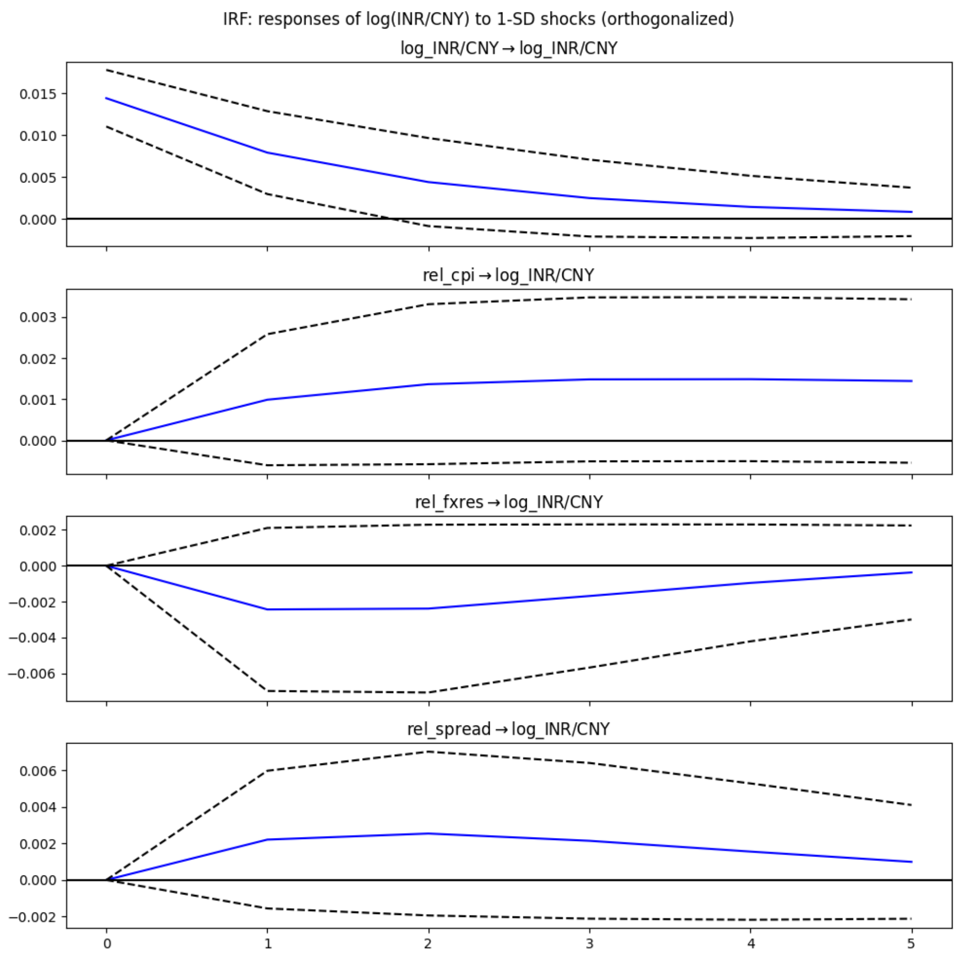
where $Z_t = (y_t, X_t)$ and $\beta' Z_t$ gives the cointegration vector.

2.3 Vector Autoregression (VAR)

When no strong cointegration is detected, a VAR in differences can be used:

$$Y_t = c + \sum_{i=1}^{p} A_i Y_{t-i} + \varepsilon_t,$$

where $Y_t = (\Delta y_t, \Delta X_t)'$. Impulse Response Functions (IRF) and Forecast Error Variance Decomposition (FEVD) help understand dynamic responses.



2.4 ARIMAX

An ARIMAX model allows explicit exogenous regressors:

$$y_t = \phi(L)(1-L)^d y_t + \theta(L)\varepsilon_t + \beta' X_t.$$

Here, X_t includes Brent, Copper, DXY returns.

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                               SARIMAX Results
==============================================================================
Dep. Variable:          ret_INRCNY=X   No. Observations:                  723
Model:                SARIMAX(2, 0, 0)   Log Likelihood                2869.659
Date:                 Wed, 27 Aug 2025   AIC                          -5727.318
Time:                         01:59:34   BIC                          -5699.834
Sample:                              0   HQIC                         -5716.708
                                 - 723
Covariance Type:                   opg
====================================================================================
                       coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------------
ret_dxy             -0.0132      0.035     -0.381      0.704      -0.081       0.055
ret_Brent_Oil        0.0019      0.009      0.227      0.820      -0.015       0.019
ret_Comex_Copper     0.0063      0.011      0.555      0.579      -0.016       0.029
ar.L1               -0.3222      0.025    -12.871      0.000      -0.371      -0.273
ar.L2               -0.1277      0.028     -4.591      0.000      -0.182      -0.073
sigma2            2.044e-05    6.4e-07     31.920      0.000    1.92e-05    2.17e-05
===================================================================================
Ljung-Box (L1) (Q):                   0.01   Jarque-Bera (JB):               463.47
Prob(Q):                              0.93   Prob(JB):                         0.00
Heteroskedasticity (H):               2.54   Skew:                            -0.32
Prob(H) (two-sided):                  0.00   Kurtosis:                         6.88
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
Forecast ret: -0.0008403432858740897
CI:      lower ret_INRCNY=X  upper ret_INRCNY=X
723           -0.009701              0.00802
```

2.5 Volatility Modelling (GARCH with Exogenous Variables)

Conditional volatility was explored with GARCH:

$$y_t = \mu_t + \varepsilon_t, \quad \varepsilon_t \sim N(0, h_t),$$

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} + \gamma' X_t.$$

This allows external drivers like DXY to affect volatility.

3 Hybrid VAR + XGBoost Residual Correction

3.1 Motivation

While VAR captures linear dependence, its residuals often show nonlinear structure. We therefore train an XGBoost model on VAR residuals using lagged values of INR/CNY, Brent, Copper, and DXY:

$$\hat{\varepsilon}_t = f_{\text{XGB}}(y_{t-1}, X_{t-1}, \dots).$$

	ret_INRCNY=X
2025-08-08	0.361190
2025-08-11	1.040769
2025-08-12	1.106391
2025-08-13	0.964872
2025-08-14	0.999790
2025-08-15	1.005232
2025-08-18	0.998177
2025-08-19	0.999807
2025-08-20	1.000333
2025-08-21	0.999931

3.2 Implementation

1. Fit VAR to INR/CNY with Brent, Copper, DXY.
2. Obtain in-sample residuals ε_t.
3. Train XGBoost on lagged features $\rightarrow$ predict $\hat{\varepsilon}_t$.
4. Hybrid forecast:
$$\hat{y}_t^{Hybrid} = \hat{y}_t^{VAR} + \hat{\varepsilon}_t^{XGB}.$$

4 Conclusion

This project compared multiple forecasting frameworks:

- VECM captured long-run relationships but struggled in out-of-sample forecasts.
- VAR provided stable forecasts but limited in handling nonlinearities.
- ARIMAX allowed flexible inclusion of global variables.
- GARCH captured conditional volatility.
- Hybrid VAR + XGBoost improved forecast accuracy by correcting systematic residual patterns.

Future extensions: include policy dummy shocks, explore LSTM/Transformer models, and expand the dataset.

References

1.Yahoo finance, Reserve Bank Of India Website, National Bureau of Statistics, China for the data.

2.Long, S., Zhang, M., Li, K. et al. Do the RMB exchange rate and global commodity prices have asymmetric or symmetric effects on China's stock prices?. Financ Innov 7, 48 (2021). https://doi.org/10.1186/s40854-021-00262-0

3. Econometric Analysis by Greene

4.Exchange Rates and International Finance by Laurence Copeland