

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

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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:

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

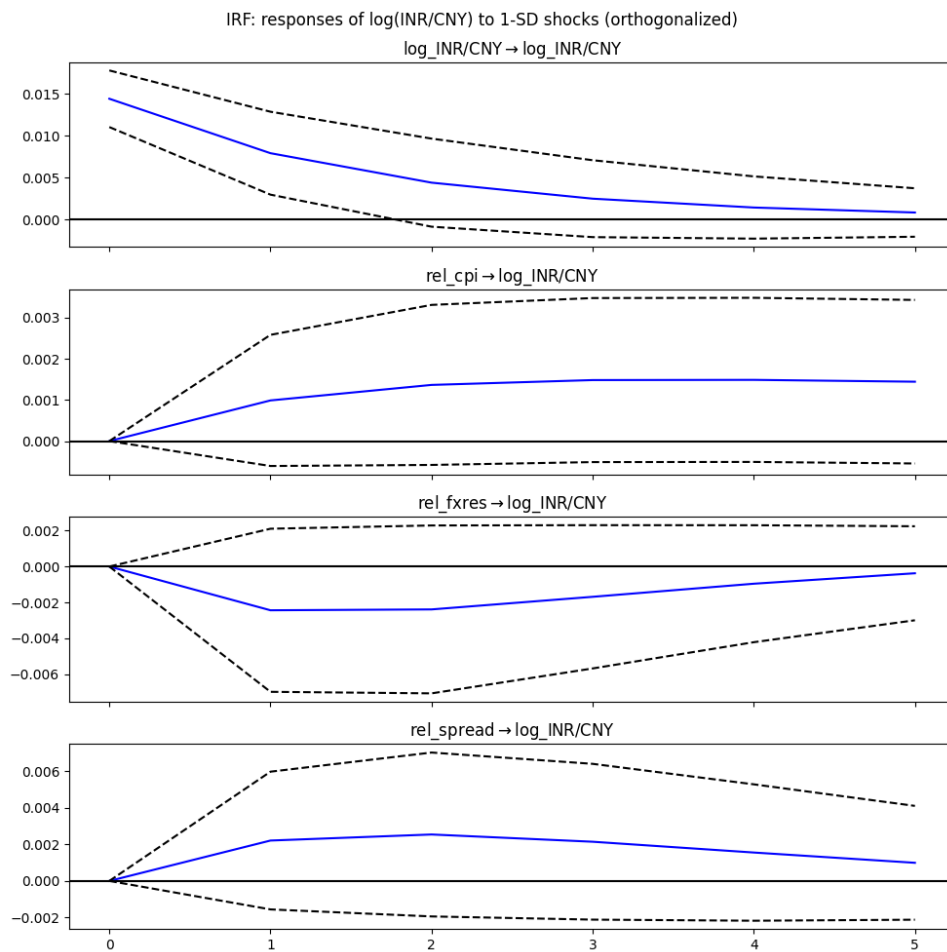
where $Z_t = (y_t, X_t)$ and $\beta' Z_t$ gives the cointegration vector.

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.

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

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