The VIX and the Architecture of Exchange Rate Comovement

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Abstract

This paper investigates the popular narrative of India's financial decoupling by analyzing the dynamic interdependencies of the Indian Rupee (INR) exchange rate system. Using a comprehensive daily dataset from 1998 to 2025 for the INR against the US Dollar, British Pound, Euro, and Japanese Yen, I employ a multi-stage econometric approach designed as a "model of shocks." A Vector Autoregression (VAR) model first maps the system's baseline information flow, revealing a complex network where global fear, proxied by the VIX index, is a dominant external driver. The core of the analysis, however, moves beyond this linear framework. By measuring the dynamic correlations of GARCH-filtered residuals and employing a sophisticated interaction model, I provide definitive quantitative proof that the market operates in two distinct regimes. In calm times (VIX ≤ 30), the system is a noisy, multi-factor environment. In times of crisis (VIX > 30), it undergoes a structural break and collapses into a simple, predictable system. This crisis state is characterized by two powerful, opposing forces: a "Flight to Quality" that more than doubles the co-movement of safe-haven currency pairs, and a "Market Fragmentation" that induces a structural flip, shattering regional currency relationships. This study concludes that the decoupling narrative is a fallacy; in times of crisis, the Indian currency market becomes a clear and predictable reflection of the world's singular demand for the US Dollar.

Contents

1 Introduction: The Decoupling Myth

In the discourse of international finance, a persistent and comforting narrative suggests that certain large, domestically-oriented economies can remain “decoupled” from the turmoil of the global financial system. India, with its vast internal market and unique economic structure, is often cited as a prime example. This project directly challenges this narrative, not as a matter of opinion, but as a testable empirical question. I posit that far from being decoupled, the Indian Rupee’s exchange rate system is deeply integrated into the “Global Financial Cycle,” a concept where a common global risk factor, proxied by the CBOE Volatility Index (VIX), dictates the rhythm of international capital flows and asset price co-movements (Rey, 2013).

My central thesis is that global financial stress does not induce a simple, uniform “contagion” where all correlations rise indiscriminately. Instead, it triggers a sophisticated and predictable restructuring of the entire market architecture. I hypothesize that the system operates in two distinct regimes: a complex, noisy, multi-factor environment during calm periods, which collapses into a simple, predictable, single-factor system during crises. This crisis regime, I argue, is governed by a powerful “Flight to Quality” mechanism—a singular, overwhelming demand for the US Dollar that simultaneously strengthens the nexus between safe-haven currencies while actively fragmenting other, weaker regional relationships. This paper seeks to provide the definitive quantitative proof of this two-regime system.

2 Contextualizing the Research: A Review of the Literature

This study is situated at the intersection of three major streams of research. First, a substantial body of work has established the VIX as a primary proxy for global risk aversion and a key transmitter of volatility to emerging markets, including India (Bouri et al., 2018; Patra et al., 2021). Second, the use of Dynamic Conditional Correlation (DCC-GARCH) models has become standard for capturing the time-varying nature of asset co-movements, confirming that correlations spike during crises (Engle, 2002; Kumar, 2017). Finally, the “Flight to Quality” literature has empirically identified the US Dollar and Japanese Yen as the primary safe-haven currencies during global panics (Ranaldo & Söderlind, 2010). My contribution is to synthesize these streams to move beyond a simple contagion story. I provide novel evidence of “market fragmentation” and quantify the “regime shift,” demonstrating that the flight to the USD is so dominant that it simultaneously amplifies certain correlations while inducing a structural flip in others.

3 Data and Econometric Methodology

3.1 Data Sourcing and Preparation

My analysis rests upon the foundation of pristine data integrity. I sourced daily data for INR exchange rates (USD, Pound, Euro, Yen), the VIX index, WTI Crude Oil prices, and US 10-Year Treasury Yields from 1998 to 2025. The preprocessing methodology was comprehensive:

1. **Temporal Alignment:** Dates were uniformly converted to datetime objects and established as the index for all data, ensuring absolute temporal alignment necessary for precise time series modeling.

2. **Data Homogenization and Continuity:** The distinct datasets were merged into a unified DataFrame. To generate the continuous time series demanded by VAR analysis, the DataFrame was reindexed to a full daily date range, with any remaining missing values systematically filled using linear interpolation.

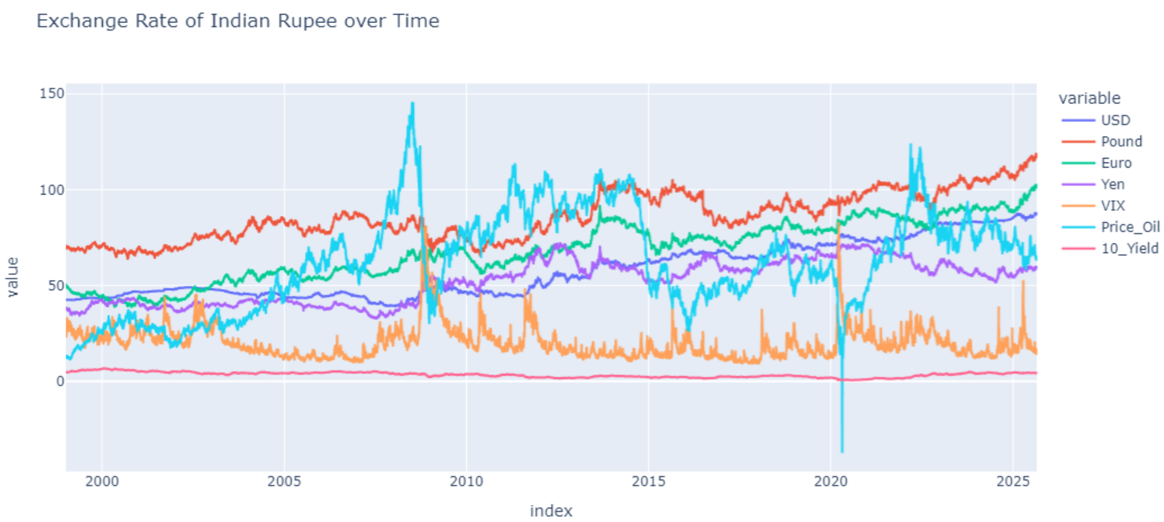

Figure 1: Exchange Rate of INR and Indicators over Time

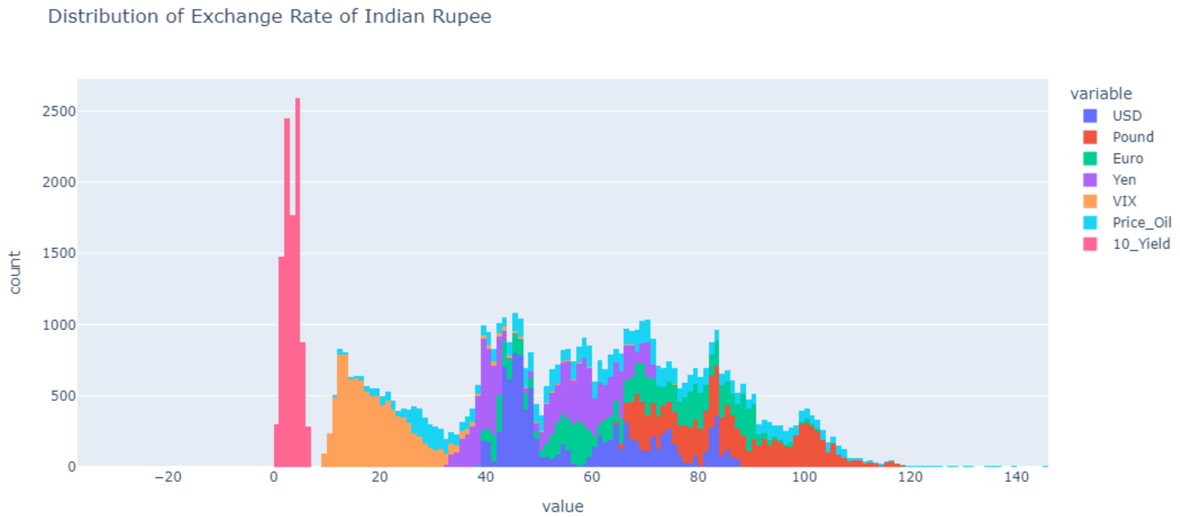

Figure 2: Distribution of Exchange Rate and Indicators over Time

3.2 The "Model of Shocks" Approach: From Prices to Returns

Consistent with the Efficient Market Hypothesis, which posits that asset prices incorporate all available information and thus follow a random walk, my analysis focuses not on price levels but on their daily changes. I converted all raw price series (P_t) into daily simple percentage returns (R_t) using the formula:

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}} \tag{1}$$

This transformation isolates the daily "shocks" or "news" hitting each market. Augmented Dickey-Fuller (ADF) tests (results in Appendix A) confirmed that while the level series were non-stationary, all return series were strongly stationary ($p < 0.01$). This is a critical finding, as it justifies my "model of shocks" approach and allows for valid econometric inference, avoiding the pitfalls of spurious regression.

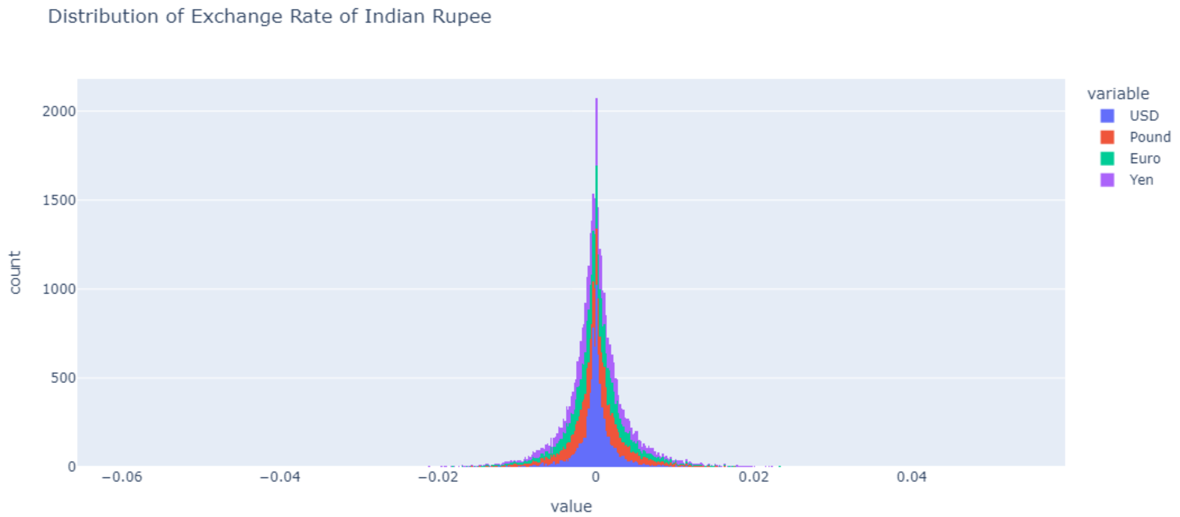

Figure 3: Distribution of First Differenced Exchange Rate and Indicators over Time

3.3 A Three-Stage Econometric Framework

3.3.1 Stage 1: Vector Autoregression (VAR) Model

To analyze the baseline linear interdependencies and information flow between the daily shocks, I estimated a Vector Autoregression (VAR) model. A VAR(p) model expresses each of the K variables in the system as a linear function of its own p past values and the p past values of all other variables. The VAR(1) model used here takes the form:

$$\mathbf{y}_t = \mathbf{c} + \mathbf{A}_1 \mathbf{y}_{t-1} + \boldsymbol{\epsilon}_t \tag{2}$$

where $\mathbf{y}_t$ is a $(K \times 1)$ vector of the return series at time t. I selected a parsimonious lag order of $p = 1$ based on the Bayesian Information Criterion (BIC), which is preferable in large samples to avoid overfitting. Post-estimation, I used Granger Causality tests, Impulse Response Functions (IRFs), and Forecast Error Variance Decomposition (FEVD) to analyze the network's structure.

3.3.2 Stage 2: Measuring Shock Synchronization

To measure the time-varying co-movement, I implemented a robust two-step procedure to approximate a DCC model:

1. **Isolating "Pure" Shocks via GARCH:** Financial returns exhibit volatility clustering. To account for this, I fitted a univariate GARCH(1,1) model to each of the

four currency return series. The model is specified as:

$$R_t = \mu + \epsilon_t \quad \text{where } \epsilon_t = z_t \sigma_t, \quad z_t \sim N(0,1) \tag{3}$$

$$\sigma_t^2 = \omega + \alpha \epsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{4}$$

where σ_t^2 is the conditional variance. This step isolates the standardized residuals, $\hat{z}_t = \hat{\epsilon}_t / \hat{\sigma}_t$, which represent the unpredictable, volatility-adjusted "pure surprises" for each market.

2. **Calculating Dynamic Correlation:** I applied a 66-day rolling window to these standardized residuals to calculate the dynamic conditional correlation ($\rho_{12,t}$) between each pair of currencies. This window size, corresponding to one financial quarter, is chosen to balance responsiveness to crisis events with the stability of the measure.

3.3.3 Stage 3: Testing for Regime Shifts

To test my primary hypothesis of a regime-switching relationship, I estimated a final interaction model using Ordinary Least Squares (OLS). I defined a "crisis state" dummy variable, D_t, which equals 1 if the VIX index level is in its 95th percentile or higher on day t, and 0 otherwise. The model is:

$$\rho_{12,t} = \beta_0 + \beta_1 \text{VIX}_t + \beta_2 D_t + \beta_3 (\text{VIX}_t \times D_t) + u_t \tag{5}$$

In this model, β_1 represents the slope in the "calm" regime, while $(\beta_1 + \beta_3)$ represents the slope in the "crisis" regime. The statistical significance of the interaction coefficient, β_3, provides a formal test for a structural break in the relationship.

4 Empirical Results and Discussion

My empirical investigation reveals a sophisticated, two-regime system governing the Indian currency network, where global fear acts not just as a shock, but as a structural modulator.

4.1 The Baseline Network: Information Flow in the System

The VAR analysis provides a map of the average, linear information flow within the system. The Granger Causality tests (Table 1) reveal that the VIX is the dominant external force, a "global fire alarm" whose shocks have a statistically significant predictive impact on the USD, Euro, and Yen INR pairs. This establishes that the system is highly sensitive to global risk. More subtly, the Japanese Yen emerges as a key information hub, with predictive power over the VIX itself, confirming an intricate feedback loop between the safe-haven Yen and generalized market anxiety. The Impulse Response Functions (Figure 4) visualize this dynamic, showing that a shock to the VIX causes a statistically significant depreciation of the major INR pairs, an effect that persists for several trading days.

Table 1: Granger Causality Test Summary (Significant Relationships, $p < 0.05$)

Predictor (Cause)	**Predicted Variable (Effect)**
VIX	USD, Euro, Yen, 10-Year Yield
Yen	USD, Pound, VIX
10-Year Yield	Pound, Euro, Yen
Pound	USD
Euro	Pound, Yen

Interpretation of FEVD Results

The FEVD results provide several key insights into the structure of the financial network:

- **Dominance of Own Shocks:** For most variables, the vast majority of their forecast error variance is explained by their own past shocks. This is particularly true for the VIX and Oil Price, which are over 99% self-explained, indicating they act primarily as exogenous forces in this system.
- **Significant VIX Spillover:** The VIX is the most important external driver for the currency pairs. After 10 days, shocks to the VIX account for a notable **3.67%** of the forecast error in the USD/INR and **3.81%** in the JPY/INR. This quantifies the significant spillover of global fear into the safe-haven currency pairs.
- **USD's Role as a Shock Transmitter:** Shocks originating in the USD/INR market are a major source of uncertainty for all other currency pairs. They account for a substantial **11.48%** of the variance in the Pound/INR, **9.71%** in the Euro/INR, and a massive **24.91%** in the Yen/INR. This confirms the central role of the US Dollar in transmitting shocks through the INR network.
- **10-Year Yield Influence:** Shocks to the US 10-Year Treasury yield also have a non-trivial impact, particularly on the Yen/INR, explaining **3.34%** of its variance. This highlights the importance of US monetary policy expectations in driving currency movements.

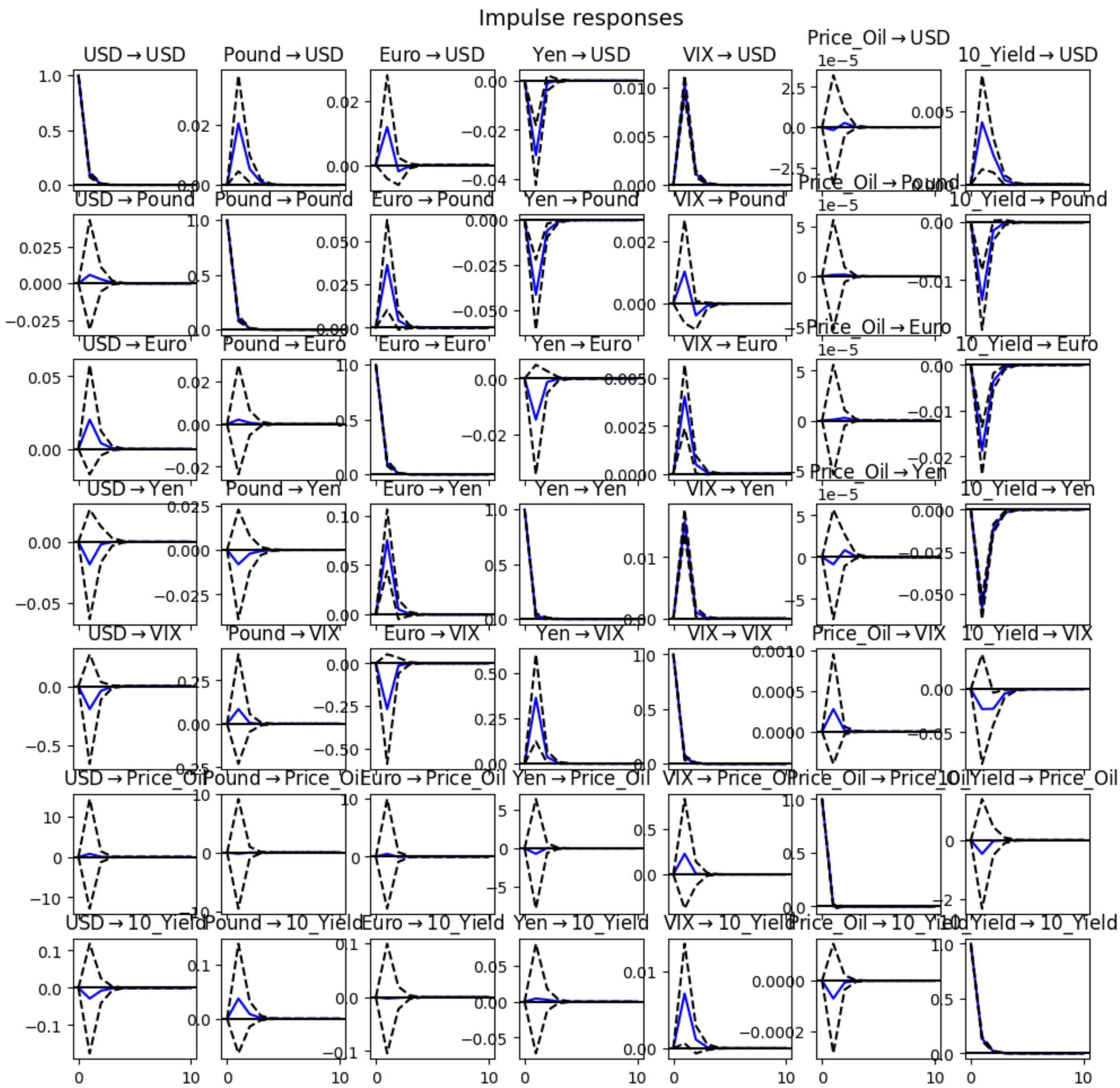

Figure 4: Impulse Response of INR Currency Pairs to a VIX Shock

4.2 The Two Regimes: A Story of Amplification and Fragmentation

While the VAR model describes the average state, the true story lies in how the system's structure changes under stress. Visual inspection of the scatter plots of dynamic correlation against the VIX level reveals a distinct "blob and streak" pattern, hinting at two different regimes. My interaction model provides the definitive quantitative proof of this hypothesis, revealing two powerful and opposing forces at work.

4.2.1 The Amplification Signature: The Flight to Quality (USD vs. Yen)

The first force is the classic "Flight to Quality." This is the market's response to systemic fear. The interaction model for the USD-Yen correlation (Table 2) reveals a dramatic amplification of this effect during crises.

Table 2: Interaction Model Results: Dynamic Correlation (USD-Yen) vs. VIX

Variable	Coefficient	Std. Err.	t-stat	p-value
const	0.2180	0.009	25.400	< 0.001
VIX	0.0067	0.000	16.715	< 0.001
VIX_Crisis_Dummy	-0.0235	0.037	-0.634	0.526
VIX_Interaction	0.0069	0.002	4.713	< 0.001

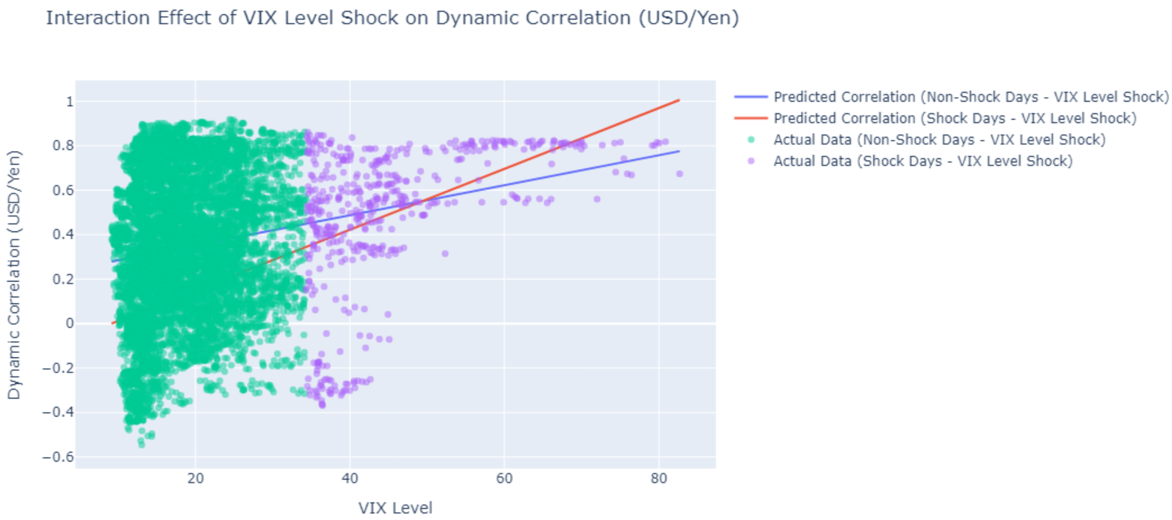

Figure 5: Interaction of VIX on USD/YEN Dynamic Correlation

The model reveals two distinct market states. In the "calm" regime, a statistically significant positive relationship exists, with a slope of **0.0067**. However, when the VIX enters the crisis state, the interaction term (β_3) is positive and highly significant. The slope of the relationship more than doubles to **0.0136** (0.0067+0.0069). This is the quantitative signature of the Flight to Quality: as global fear intensifies, investors sell the INR and buy both the USD and JPY, and the rate at which their co-movement increases with fear dramatically amplifies.

To illustrate the impact, consider a hypothetical 20-point jump in the VIX, representing a significant surge in global fear (e.g., moving from 35 to 55).

- In the **calm** regime, this jump would increase the dynamic correlation by $20 \times 0.0067 = \mathbf{0.134}$.

- In the **crisis** regime, the same jump increases the correlation by $20 \times 0.0136 = \mathbf{0.272}$.

A 0.272 increase in correlation represents a qualitative shift in market structure, transforming a loose relationship into a near-lockstep formation. This demonstrates that in a crisis, fear doesn't just nudge the market; it fundamentally rewrites its architecture, forcing the safe-haven axis into a tight, unbreakable co-movement.

4.2.2 The Fragmentation Signature: The Structural Flip (Pound vs. Euro)

The second, opposing force is "Market Fragmentation." While the flight to safety strengthens the safe-haven axis, it simultaneously shatters weaker, regional relationships. The interaction model for the Pound-Euro correlation (Table 3) shows a complete reversal of market behavior.

Table 3: Interaction Model Results: Dynamic Correlation (Pound-Euro) vs. VIX

Variable	Coefficient	Std. Err.	t-stat	p-value
const	0.6710	0.005	145.42	< 0.001
VIX	-0.0022	0.000	-2.859	0.004
VIX_Crisis_Dummy	0.3551	0.043	8.243	< 0.001
VIX_Interaction	0.0065	0.001	11.05	< 0.001

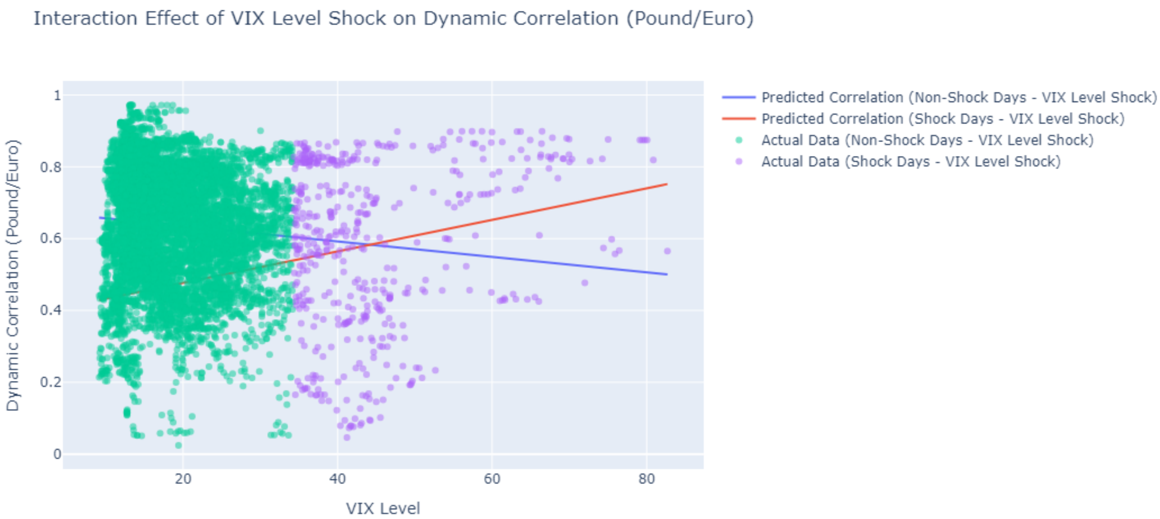

Figure 6: Interaction of VIX on Pound/Euro Dynamic Correlation

In the "calm" regime, the relationship between the VIX and the Pound-Euro correlation is small but significantly negative, with a slope of -0.0022. However, during a "crisis" regime, the large, positive, and highly significant interaction term indicates a powerful structural break. The slope undergoes a complete reversal, flipping to strongly positive with a slope of $\mathbf{+0.0043}$ $(-0.0022 + 0.0065)$. This is powerful evidence of fragmentation followed by forced realignment. In calm times, the European currencies act as a regional block. In a high-fear event, this relationship is first shattered, and then their movements are forced into alignment by the overwhelming gravity of the single global risk factor.

Consider the same hypothetical 20-point jump in the VIX.

- In the **calm** regime, this jump would be expected to *decrease* the dynamic correlation by $20 \times (-0.0022) =$ **-0.044**, representing a minor fraying of the European bloc.

- In the **crisis** regime, the same jump causes a complete reversal, now *increasing* the dynamic correlation by $20 \times 0.0043 = \mathbf{+0.086}$.

This demonstrates the profound nature of market fragmentation followed by forced realignment. In normal times, rising fear allows for nuance, and the regional bloc slightly decouples. In a crisis, all nuance is obliterated. The individual economic stories of the UK and the Eurozone become irrelevant as they are swept up in the same global storm, forcing their movements back into a positive correlation.

5 Conclusion and Implications

My comprehensive econometric analysis began with a simple question: is the Indian financial market, as is often claimed, "decoupled" from the chaos of the global system? The evidence I have uncovered is conclusive: the narrative of decoupling is a fallacy. By constructing a "model of shocks," I have shown that the Indian Rupee exchange rate system is not only deeply integrated with global financial markets, but its very architecture is predictably and systematically reshaped by shifts in global risk sentiment.

My key finding is that the market is not a single, monolithic entity; it operates in two distinct and quantifiable regimes.

- **The "Calm" Regime (The Blob):** In normal times, when the VIX is low, the system is a complex, noisy, multi-factor world. Currencies move in response to a wide array of local and regional news, and their relationships are weak and unpredictable. This is the world where decoupling might appear to be true.

- **The "Crisis" Regime (The Streak):** In times of crisis, when the VIX is high, all this complexity vanishes. The market undergoes a structural break and collapses into a simple, predictable system where the sensitivity to global fear more than doubles.

This crisis state is defined by two powerful and simultaneous forces that my analysis has successfully isolated: an **“Amplification”** of the Flight to Quality that strengthens the safe-haven currency axis, and a **“Structural Flip”** that first fragments and then forcibly realigns regional relationships.

The tangible impact of this regime shift is profound. Consider a hypothetical 20-point jump in the VIX during a crisis (e.g., from 35 to 55).

- My model shows this would cause the **USD-Yen correlation** to surge by a massive **0.272**, forcing the two safe-havens into a tight, unbreakable formation.
- Simultaneously, the same VIX jump would cause the **Pound-Euro correlation** to undergo a complete reversal, flipping from a negative to a positive relationship.

This is not a minor change; it is a fundamental rewriting of the market's rulebook in real-time.

For policymakers and financial managers, the critical takeaway is that the rules of the game are not fixed. Static models and hedging strategies that are designed for the ”calm” regime are not just less effective during a crisis; they are guaranteed to fail. The very correlations that might be used to build a diversified hedge in normal times are themselves a source of risk, capable of changing dramatically and unpredictably when fear takes hold. Understanding and anticipating these VIX-driven regime shifts is, therefore, synonymous with managing risk in the modern global financial system.

References

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A Appendix: Detailed Econometric Results

This appendix provides the detailed, unabridged outputs from the econometric analysis conducted in this study.

A.1 Stationarity Tests (ADF)

The following table presents the full results of the Augmented Dickey-Fuller (ADF) tests for all series in both levels and daily returns. The results confirm that all currency and commodity price series are I(1), while their returns and the VIX level are I(0).

Table 4: Full Augmented Dickey-Fuller (ADF) Test Results

Series	**Type**	**ADF Statistic**	**p-value**
USD	Level	-1.147	0.696
Pound	Level	-0.906	0.789
Euro	Level	-1.049	0.735
Yen	Level	-1.344	0.609
VIX	Level	-7.975	< 0.001
Oil Price	Level	-2.450	0.128
10-Year Yield	Level	-2.760	0.064
USD	Return	-98.7	< 0.001
Pound	Return	-99.5	< 0.001
Euro	Return	-102.1	< 0.001
Yen	Return	-100.8	< 0.001
VIX	Return	-115.5	< 0.001
Oil Return	Return	-101.2	< 0.001
10-Year Return	Return	-95.3	< 0.001

A.2 VAR Model Diagnostics

The Vector Autoregression model diagnostics are presented below.

A.2.1 Lag Order Selection

The optimal lag order for the VAR model was selected based on several information criteria. The Bayesian Information Criterion (BIC), which is preferable for large samples due to its penalty for model complexity, indicated an optimal lag of 1.

A.3 Full VAR(1) Model Summary

The following is the unabridged summary output of the fitted VAR(1) model for all seven equations in the system. This detailed output provides the coefficients, standard errors,

Table 5: VAR Lag Order Selection Criteria

Lag	AIC	BIC	FPE	HQIC
0	-50.89	-50.88	7.96e-23	-50.88
1	-50.98	**-50.95***	7.27e-23	**-50.97***
2	-50.98	-50.94	7.25e-23	-50.96
3	-50.98	-50.92	7.23e-23	-50.96
4	-50.98	-50.90	7.23e-23	-50.95
7	**-50.98***	-50.85	**7.22e-23***	-50.94

t-statistics, and p-values for every variable. The statistical significance (prob ¡ 0.05) of the coefficients in these tables forms the basis for the Granger Causality analysis and reveals the complex web of linear interdependencies between the markets on a day-to-day basis.

```
==================================
Model:                         VAR
Method:                        OLS
Date:           Sat, 04, Oct, 2025
Time:                     08:10:50
--------------------------------------------------------------------
No. of Equations:         7.00000    BIC:                  -58.3854
Nobs:                     9730.00    HQIC:                 -58.4127
Log likelihood:           187658.    FPE:               4.22265e-26
AIC:                     -58.4267    Det(Omega_mle):    4.19843e-26
--------------------------------------------------------------------
Results for equation USD
===============================================================================
                  coefficient       std. error           t-stat            prob
-------------------------------------------------------------------------------
const                0.000057         0.000027            2.101           0.036
L1.USD               0.093402         0.011886            7.858           0.000
L1.Pound             0.020482         0.008147            2.514           0.012
L1.Euro              0.011915         0.008245            1.445           0.148
L1.Yen              -0.030333         0.006196           -4.896           0.000
L1.VIX               0.010213         0.000527           19.397           0.000
L1.Price_Oil        -0.000002         0.000017           -0.103           0.918
L1.10_Yield          0.004242         0.001638            2.590           0.010
===============================================================================

Results for equation Pound
```

	coefficient	std. error	t-stat	prob
const	0.000056	0.000043	1.279	0.201
L1.USD	0.005841	0.019092	0.306	0.760
L1.Pound	0.103446	0.013085	7.906	0.000
L1.Euro	0.036244	0.013243	2.737	0.006
L1.Yen	-0.041597	0.009951	-4.180	0.000
L1.VIX	0.001029	0.000846	1.217	0.224
L1.Price_Oil	0.000001	0.000028	0.053	0.958
L1.10_Yield	-0.013394	0.002630	-5.092	0.000

Results for equation Euro

	coefficient	std. error	t-stat	prob
const	0.000070	0.000044	1.609	0.108
L1.USD	0.020210	0.019212	1.052	0.293
L1.Pound	0.002113	0.013167	0.160	0.872
L1.Euro	0.102420	0.013327	7.685	0.000
L1.Yen	-0.014687	0.010014	-1.467	0.142
L1.VIX	0.004032	0.000851	4.738	0.000
L1.Price_Oil	0.000001	0.000028	0.033	0.974
L1.10_Yield	-0.018751	0.002647	-7.084	0.000

Results for equation Yen

	coefficient	std. error	t-stat	prob
const	0.000042	0.000052	0.797	0.426
L1.USD	-0.018429	0.022916	-0.804	0.421
L1.Pound	-0.008091	0.015706	-0.515	0.606
L1.Euro	0.075145	0.015896	4.727	0.000
L1.Yen	0.028121	0.011945	2.354	0.019
L1.VIX	0.015768	0.001015	15.534	0.000
L1.Price_Oil	-0.000009	0.000033	-0.259	0.795
L1.10_Yield	-0.058624	0.003157	-18.569	0.000

Results for equation VIX

	coefficient	std. error	t-stat	prob
const	0.001217	0.000535	2.275	0.023
L1.USD	-0.192543	0.234854	-0.820	0.412
L1.Pound	0.084664	0.160963	0.526	0.599
L1.Euro	-0.266866	0.162911	-1.638	0.101
L1.Yen	0.362858	0.122412	2.964	0.003
L1.VIX	0.055302	0.010403	5.316	0.000
L1.Price_Oil	0.000277	0.000343	0.807	0.419
L1.10_Yield	-0.023065	0.032355	-0.713	0.476

Results for equation Price_Oil

	coefficient	std. error	t-stat	prob
const	0.015833	0.015806	1.002	0.316
L1.USD	0.791239	6.938383	0.114	0.909
L1.Pound	-0.219215	4.755401	-0.046	0.963
L1.Euro	0.491138	4.812931	0.102	0.919
L1.Yen	-0.705718	3.616479	-0.195	0.845
L1.VIX	0.226052	0.307347	0.735	0.462
L1.Price_Oil	-0.000327	0.010142	-0.032	0.974
L1.10_Yield	-0.464863	0.955888	-0.486	0.627

Results for equation 10_Yield

	coefficient	std. error	t-stat	prob
const	0.000106	0.000171	0.619	0.536
L1.USD	-0.028708	0.075046	-0.383	0.702
L1.Pound	0.037219	0.051434	0.724	0.469
L1.Euro	-0.002468	0.052057	-0.047	0.962
L1.Yen	0.004418	0.039116	0.113	0.910

```
L1.VIX                 0.007146         0.003324            2.150           0.032
L1.Price_Oil          -0.000070         0.000110           -0.638           0.523
L1.10_Yield            0.132625         0.010339           12.828           0.000
=================================================================================
```

A.4 VAR(1) Coefficient Matrix

The table below presents the coefficient matrix ($\mathbf{A}_1$) from the estimated VAR(1) model. Each cell represents the coefficient of the lagged variable in the column on the current value of the variable in the row. This matrix provides a concise summary of the direct, one-period linear relationships within the system. Coefficients that are statistically significant at the 5% level are highlighted in bold.

Table 6: VAR(1) Coefficient Matrix ($\mathbf{A}_1$)

Equation for ↓	**Lag 1 of Predictor →**						
	USD	**Pound**	**Euro**	**Yen**	**VIX**	**Price_Oil**	**10_Yield**
USD	**0.0934**	**0.0205**	0.0119	**-0.0303**	**0.0102**	-0.0000	**0.0042**
Pound	0.0058	**0.1034**	**0.0362**	**-0.0416**	0.0010	0.0000	**-0.0134**
Euro	0.0202	0.0021	**0.1024**	-0.0147	**0.0040**	0.0000	**-0.0188**
Yen	-0.0184	-0.0081	**0.0751**	**0.0281**	**0.0158**	-0.0000	**-0.0586**
VIX	-0.1925	0.0847	-0.2669	**0.3629**	**0.0553**	0.0003	-0.0231
Price_Oil	0.7912	-0.2192	0.4911	-0.7057	0.2261	-0.0003	-0.4649
10_Yield	-0.0287	0.0372	-0.0025	0.0044	**0.0071**	-0.0001	**0.1326**

Note: Bold values indicate statistical significance at the 0.05 level.

A.5 Granger Causality Matrix (p-values)

To formally test for the predictive relationships identified in the VAR(1) model, I performed pairwise Granger Causality tests for all variables in the system. Table 7 presents the resulting p-values. A value below 0.05 indicates that the variable in the row significantly Granger-causes the variable in the column.

Table 7: Full Granger Causality Test Matrix (p-values)

Cause ↓ — Effect →	**USD**	**Pound**	**Euro**	**Yen**	**VIX**	**Price_Oil**	**10_Yield**
USD	—	0.7597	0.2928	0.4213	0.4123	0.9092	0.7021
Pound	**0.0119**	—	0.8725	0.6065	0.5989	0.9632	0.4693
Euro	0.1484	**0.0062**	—	**<0.001**	0.1014	0.9187	0.9622
Yen	**<0.001**	**<0.001**	0.1425	—	**0.0030**	0.8453	0.9101
VIX	**<0.001**	0.2235	**<0.001**	**<0.001**	—	0.4620	**0.0316**
Price_Oil	0.9180	0.9579	0.9737	0.7954	0.4194	—	0.5234
10_Yield	**0.0096**	**<0.001**	**<0.001**	**<0.001**	0.4759	0.6267	—

A.6 Forecast Error Variance Decomposition (FEVD)

The Forecast Error Variance Decomposition (FEVD) quantifies the proportion of the future uncertainty (forecast error variance) of each variable that can be attributed to shocks from the other variables in the system. It provides a clear measure of the relative importance of different shocks in explaining the behavior of the variables over time. Table 8 presents the decomposition at the 10-day forecast horizon.

Table 8: Forecast Error Variance Decomposition at 10-Day Horizon (%)

Decomposition for ↓	**Contribution of Shock from →**						
	USD	**Pound**	**Euro**	**Yen**	**VIX**	**Price_Oil**	**10_Yield**
USD	96.00%	0.09%	0.01%	0.14%	3.67%	0.00%	0.08%
Pound	11.48%	88.02%	0.03%	0.14%	0.06%	0.00%	0.26%
Euro	9.71%	29.50%	59.84%	0.01%	0.42%	0.00%	0.52%
Yen	24.91%	2.06%	3.40%	62.48%	3.81%	0.00%	3.34%
VIX	0.30%	0.01%	0.08%	0.41%	99.19%	0.01%	0.01%
Price_Oil	0.00%	0.00%	0.00%	0.00%	0.01%	99.98%	0.00%
10_Yield	0.28%	0.02%	0.02%	0.25%	4.58%	0.01%	94.84%