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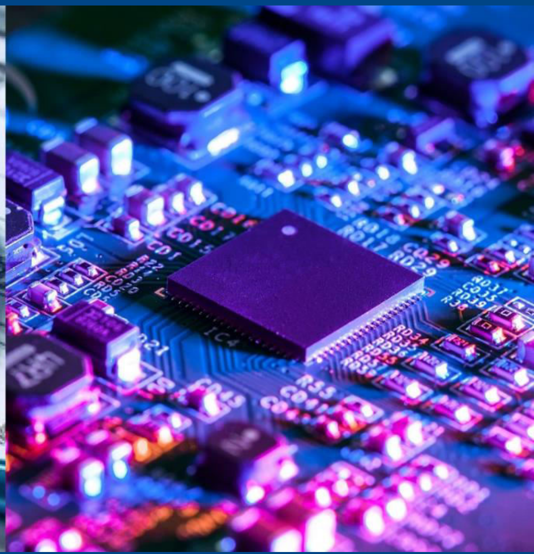

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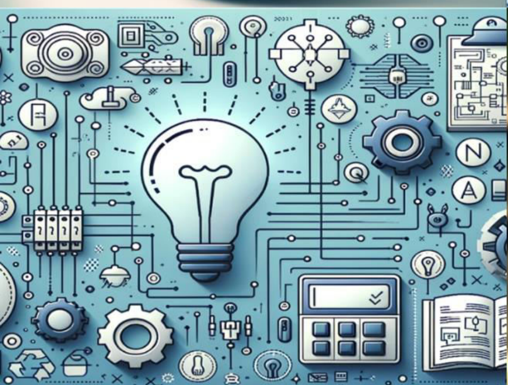

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Structural Resilience in the Indian Equity Market: Evidence of a Regime Shift in the Nifty 50–India VIX Relationship (2015–2025)

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ABSTRACT: This research aims to analyze the Nifty 50 and India VIX variables' relationship and structural shift, if any, over a period of 10 years from 2015 to 2025 by comparing Pre – Covid (2015 – 2020) and Post – Covid (2020 – 2025) relation. By using the hybrid model of OLS – ARCH – EGARCH model on the Gretl software, it has been discovered that Nifty 50's market sensitivity has dropped down by 72.3% in the post – covid era thereby signaling a transition from "crisis – prone" to "growth – resilient" structure in the Indian equity market. The findings of this research highlight a "structural buffer" that further strengthens the claim of long – term stability and "India Premium" perception for global investors.

KEYWORDS: Nifty 50, India VIX, Structural Resilience, EGARCH Model, Volatility Clustering.

I. INTRODUCTION

Over the last decade, the Nifty 50 has evolved from a volatile emerging market index at ₹7,914.35 in 2015 to a global cornerstone reaching ₹26,129.60 by 2025. This growth persisted despite domestic shocks like Demonetization and the profound global disruption of the COVID-19 pandemic, which saw the index plummet 29.35% to a March 2020 bottom of ₹8,597. While such crises traditionally triggered prolonged panic, the post-2020 era marked a structural shift where spikes in the India VIX (market fear) began to precede rapid capital growth rather than systemic collapse. This suggests a maturing "Growth-Resilient" framework where the market now absorbs shocks with greater efficiency, transitioning away from its historical "Crisis-Prone" state.

To quantify this evolution, this thesis employs a hybrid OLS-ARCH-EGARCH econometric framework to analyze the inverse relationship between the Nifty 50 and India VIX, specifically testing for structural breaks during the 2020 pandemic. By focusing on the 2023–2025 "Normalization Phase," the research investigates whether the sustained high-valuation growth of the Indian equity market represents a fundamental change in market behavior. This study aims to move beyond anecdotal evidence to determine if a "structural buffer" now supports the "India Premium," insulating the National Stock Exchange from global volatility trends through institutional stability and increased retail participation.

II. REVIEW OF LITERATURE:

Market Volatility & Efficiency

The Nifty 50 exhibits **volatility clustering**, where periods of instability persist over time. Asymmetric models like **GJR-GARCH** reveal that the Indian market is historically more sensitive to negative "shocks" than positive news. **[1]** The **India VIX** acts as a reliable "fear gauge"; its lagged returns often drive current Nifty fluctuations, serving as a short-term hedging tool for investors. **[3]**

The COVID-19 Structural Break (2020–2022)

The pandemic served as a massive stress test, causing volatility expectations to spike and breaking rational pricing mechanisms. Synchronized aggressive selloffs occurred until regulatory interventions by **SEBI** and the government stabilized the market through control measures. **[7][4]**

Post-Crisis Resilience & Growth (2023–2025)

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A historic rebound was driven by supportive policies and a surge in **retail investor participation**, leading the market to "detach" from certain global volatility trends. Volatility forecasting has matured; using **Machine Learning** and **OLS/GARCH** models, institutional investors can now better manage the volatility-return trade-off. **[5][2][6]**

Advanced Predictive Modelling
The relationship between India VIX and Nifty 50 is a constant, high-frequency technical interaction best predicted by hybrid models like **ARIMA-EGARCH**. **[8][10]** Modern volatility is highly persistent; traditional math is now being supplemented by **Deep Learning (RNNs and LSTMs)** to capture complex "non-linear" patterns. **[11][12]**

Global Integration & Macro Factors
The India VIX now moves in parallel with the **CBOE VIX**, requiring investors to account for global risk spillovers and signals from the S&P 500 and USD-INR exchange rates. India's relationship with crude oil prices has evolved, showing increased macroeconomic resilience compared to historical sensitivities. **[13][15]**

Strategic Asset Allocation
Volatility triggers a **"flight to quality,"** where capital shifts from mid-caps to stable large caps as a protective shield during downturns. By 2025, tighter synergy between spot and options markets has created a sophisticated price discovery system, providing a stable foundation for long-term capital growth. **[16][19][20]**

III. IDENTIFICATION OF RESEARCH GAPS:

Despite the existing literature on the Nifty 50 and India VIX, several critical gaps remain that this research aims to seek:
1. Temporal Limitation (2023 – 2025): A significant majority of prominent research focuses exclusively on the immediate "shock" and "recovery" periods of the 2020 pandemic. There is a lack of comprehensive analysis extending into the 2023 – 2025 era, a period where the Indian market reached record highs despite global quantitative tightening, suggesting a fundamental shift into the "India Premium".
2. Lack of Empirical Metrics for Structural Resilience: While existing studies utilize GARCH models for forecasting, they rarely employ these models to explicitly compare the "Persistence of Shocks" across distinct areas. There is a research gap in using GARCH parameters ($\alpha + \beta$) as formal metrics to prove that volatility shocks in the 2020s dissipate faster than those in the 2015 – 2019 era.
3. Institutional Volatility Dampening: The literature lacks a regression – based comparison of the "Beta of Fear" to quantify the surge in Domestic Institutional Investors (DIIs) participation has dampened the sensitivity to the India VIX compared to the Foreign Institutional Investors (FIIs) – dominated 2015 – 2019 period.
4. Functional Redefinition of VIX: Current studies treat VIX as a reactive "Fear Gauge". There is a gap in the perception of VIX being a structural precursor or a leading indicator for "Capital Growth" cycles in a maturing economy.
5. Behavioral Decoupling: Existing research has not sufficiently explored why the Nifty 50 has recently decoupled from global volatility indices. This study investigates if domestic – led efficiency has reduced the market's historic sensitivity to international shocks.

IV. RESEARCH OBJECTIVES:

The primary aim of this research is to evaluate the maturing relationship between market returns and fear – driven volatility in India. It specifically focuses on:
1. Determining the statistical strength and direction of the relationship between Nifty 50 daily returns and India VIX closing values using the OLS mean equation.
2. Investigating the existence of "Volatility Clustering" within the Indian equity market across the 2015 – 2025 timeline using the ARCH – LM diagnostic testing.
3. Assessing the "Leverage Effect" or asymmetric response of market volatility to positive and negative shocks through the application of the EGARCH model.
4. Identifying and quantifying the structural shift in market resilience by comparing the pre – pandemic and post – pandemic eras using dummy interaction terms.
5. Evaluating whether the Indian market has successfully transitioned from a crisis – reactive state to a capital growth – resilient state by examining the persistence of volatility shocks ("$\alpha + \beta$" parameters) in the GARCH framework.

V. FRAMING OF THE RESEARCH HYPOTHESES:

The following hypotheses are framed to test the validity of the OLS -ARCH – EGARCH model in capturing the market's structural transformation:

HYPOTHESIS 1: DIRECTIONAL RELATIONSHIP (OLS)

H01: There is no significant inverse relationship between India VIX levels and Nifty 50 daily returns.

Ha1: There is significant inverse relationship between India VIX levels and Nifty 50 daily returns.

HYPOTHESIS 2: VOLATILITY CLUSTERING (ARCH)

H02: The Indian equity market does not exhibit significant ARCH effects (volatility clustering) over the 2015 – 2025 period.

Ha2: The Indian equity market exhibits significant ARCH effects (volatility clustering) over the 2015 – 2025 period.

HYPOTHESIS 3: ASYMMETRY AND LEVERAGE (EGARCH)

H03: Market volatility responds symmetrically to positive and negative news shocks of equal magnitude in the Indian market.

Ha3: Market volatility exhibits an asymmetric "leverage effect", where negative shocks (market drops) increase volatility more than positive shocks.

HYPOTHESIS 4: STRUCTURAL GROWTH (Dummy Interactions)

H04: The sensitivity of the Nifty 50 to VIX spikes has remained unchanged between the pre – pandemic and post – pandemic eras.

Ha4: There is a significant structural shift in market sensitivity, with the post – pandemic era demonstrating higher resilience and faster stabilization.

RESEARCH DESIGN:

The research design for this study is Empirical, Analytical and Longitudinal. It follows a structured quantitative flow to move from a surface – level correlation to a deep – dive of market mechanics.**Empirical Approach:** The study uses actual market – generated data (secondary data) from the NSE. It avoids subjective sentiment surveys and rather relies on the "revealed preference" of the market as captured in the closing prices of the Nifty 50 and the India VIX.

Analytical Approach:

The research is designed in a three – stage econometric hierarchy:

1. **1st Stage – The Mean Model:** We begin with an **Ordinary Least Square (OLS)** regression. This is done to establish the baseline relationship. By including a dummy variable for the 2020 COVID – 19 outbreaks, we can statistically test for a structural break. This identifies if the average relationship between fear and price has shifted.
2. **2nd Stage – Diagnostic Filtering:** Prior progressing to the advanced models, the design incorporates the **ARCH – LM test**. This is a critical diagnostic step. Financial time – series data often suffers from heteroskedasticity (i.e. variance that changes over time). If the ARCH test is significant, it proves that a standard OLS is insufficient, justifying the need for GARCH – family models.
3. **3rd Stage – The Asymmetric Model:** Finally, we utilize the **Exponential GARCH (EGARCH) model**. Standard GARCH models assume that "good news" and "bad news" impact volatility identically. However, the **Leverage Hypothesis** suggests that market participants panic more during crashes. The EGARCH model is specifically designed to capture this asymmetry without the need for non – negativity constraints on parameters.

Longitudinal Approach: The design covers an eleven – year span, allowing for a longitudinal view of market maturity. The study is divided into two distinct **"eras"**: The **Pre – Covid development phase (2015 – 2019)** and the **Post – Covid growth phase (2020 – 2025)**. By comparing the coefficients of the EGARCH model across these areas, the research design provides a definitive verdict on whether the market's "memory of fear" shortened which is a primary indicator of structural growth.

Software: The research is conducted using the **Gretl software**, chosen for its robust time – series capabilities and transparent output for ARCH and EGARCH specifications.

VI. METHODS FOR DATA COLLECTION AND VARIABLES OF THE STUDY

METHOD FOR DATA COLLECTION:

This study relies exclusively on Secondary Data sourced from reputable financial databases to ensure the highest degree

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of objectivity and replicability. The primary source of data is the **National Stock Exchange (NSE) of India "official archives"**, accessed via the **Yahoo Finance (yfinance) API** and the NSE India website.
The data collection process is as follows:

1. **Extraction:** Daily closing prices of Nifty 50 index and India VIX are extracted for the period – January 1, 2015, to December 31, 2025. This ensures a **high – frequency daily observation** set accounting for approx. 2,700 trading days.
2. **Cleaning:** The raw data has then been subjected to a cleaning process using **Python (Pandas library)**. This involves **"Date Alignment"** ensuring that every Nifty 50 closing price has a corresponding India VIX value. Missing values resulting from market holidays or technical glitches are handled via listwise deletion to maintain the continuity of the time – series.
3. **Transformation:** To satisfy the assumptions of econometric modelling, the raw Nifty 50 prices are transformed into **Daily Log Returns**. This transformation is necessary because the raw stock prices are usually "non – stationary", which can lead to spurious regression. Log returns stabilize the mean and variance, making the data suitable for OLS and EGARCH analysis.

VII. VARIABLES UNDER STUDY

The study uses three primary categories of variables:

1. **Dependent Variable: Nifty 50 Log Returns (Rt)**

The Nifty 50 is the benchmark index of the Indian equity market, representing 50 of the largest stocks. For this study, the variable is defined as the first difference of the natural log of the closing price:

Rt = ln(Pricet / Pricet-1)

Using log returns allows the research to measure the rate of capital growth and ensures the data is stationary, as confirmed by the **Augmented Dickey – Fuller (ADF) test**.

2. **Independent Variable: India VIX Closing Values (VIXt)**

The India VIX is the primary "Fear Gauge" of the Indian market. Unlike the Nifty 50, which measures price, the VIX measures the Implied Volatility derived from Nifty 50 index options. It represents the market's expectation of volatility over the next 30 days. In our study, the VIX is used in its raw level form because it is naturally mean – reverting and stationary, as proven by our diagnostic tests. It serves as the proxy for market uncertainty and crisis intensity.

3. **Dummy Variable: Covid Era (Dt)**

To address the **"Pre & Post Covid"** aspect of the thesis, a **binary dummy variable** is introduced:

Dt = 0 for observations between January 2015 and February 2020.

Dt = 1 for observations from March 2020 to December 2025. - This variable allows the OLS and EGARCH models to estimate if there was a "intercept shift" or a "slope change" in the market's behavior following the pandemic shock.

4. **Interaction Variable: VIXt . Dt**

A derived variable created by multiplying the VIX value by the Dummy Variable. This is the most critical variable for assessing the Structural Growth. The coefficient of this interaction term tells us if the sensitivity of the Nifty 50 to VIX spikes has changed in the post – pandemic era.

VIII. TECHNIQUES FOR DATA ANALYSIS

This study is built upon a hierarchical econometric approach, moving from basic descriptive measures to advanced asymmetric modelling. This process ensures that the final results are not only statistically significant but also theoretically robust against the unique "noise" of financial time – series data.

1. **Descriptive Statistics and Diagnostic Preliminaries:**

The analysis begins with finding out the central tendency and dispersion metrics – Mean, Median, Standard Deviation, Skewness and Kurtosis. Given the high – frequency nature of Nifty 50 and India VIX data, financial returns often exhibit "fat tails" or leptokurtosis. Establishing these baseline statistics is the first step in identifying the "volatility clustering".

2. **The Stationarity Test (Augmented Dickey – Fuller Test – ADF):**

To prevent spurious regression (where two unrelated variables appear related), the ADF test is applied. Since raw equity prices like the Nifty 50 are typically non – stationary, they are transformed into log returns. This transformation stabilizes

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the mean and variance, which is mandatory for any GARCH – family model.

3. **The Mean Equation (Ordinary Least Squares – OLS):**

In order to identify the directional relationship, OLS regression is the primary technique used. The model follows the equation:

$$R_t = \alpha + \beta_1(VIX_t) + \beta_2(D_t) + \beta_3(VIX_t \, . \, D_t) + \varepsilon_t$$

Where,

Rt = Nifty 50 Log Returns

VIXt = Indian VIX Closing Values **Dt** = Covid Era Dummy Variable **VIXt . Dt** = Interaction Term

This technique allows for the estimation of the "Beta of Fear". The inclusion of the interaction term specifically targets the structural shift by measuring if the Nifty's sensitivity to the VIX changed after the 2020 pandemic.

4. **ARCH – LM Diagnostic Filtering:**

Before advancing to advanced volatility models, we apply the ARCH Lagrange Multiplier test. This acts as a diagnostic gatekeeper. It checks if the errors from our OLS model are independent or if they cluster together. If cluster is present, it proves that the market has a memory of shocks, providing the academic justification for EGARCH model.

5. **Exponential GARCH (EGARCH) Modelling:**

The core analytical technique is the EGARCH(1,1) model. Unlike standard models, EGARCH is used here because it does not require the parameters to be non – negative and capture "asymmetry". This technique allows the research to quantify the Leverage Effect i.e. testing if the Indian market reacts more violently to negative volatility shocks than to positive ones.

6. **Comparative "Era" Analysis:**

The data is analyzed across two distinct "eras": the Pre – Covid (2015 – 2019) and Post – Covid (2020 – 2025) phases. By comparing the "Persistence Parameters" of the EGARCH model across these periods, the study determines if the market's recovery speed has structurally improved.

DATA STATIONARITY TEST

We conduct the Augmented Dickey – Fuller test to ensure that our time – series variables do not possess a "Unit Root", which would lead to spurious results. This test is essential prior proceeding with the advanced hybrid OLS – ARCH – EGARCH model.

H0: The time – series has a unit root i.e. the series is non – stationary.

Ha: The time – series does not have a unit – root i.e. the series is stationary.

Augmented Dickey-Fuller test for VIX_Value testing down from 27 lags, criterion AIC sample size

2666

unit-root null hypothesis: a = 1

test with constant

including 23 lags of (1-L)VIX_Value model: (1-L)y = b0 + (a-1)*y(-1) + ... + e estimated value of

(a - 1): -0.0170765 test statistic: tau_c(1) = -4.45313 asymptotic p-value 0.0002337

1st-order autocorrelation coeff. for e: 0.001

lagged differences: F(23, 2641) = 4.414 [0.0000]

Augmented Dickey-Fuller test for Nifty_Log_Return

testing down from 27 lags, criterion AIC sample size 2674

unit-root null hypothesis: a = 1

test with constant

including 15 lags of (1-L)Nifty_Log_Return model: (1-L)y = b0 + (a-1)*y(-1) + ... + e estimated value of (a - 1): -0.981537

test statistic: tau_c(1) = -13.1154 asymptotic p-value 2.568e-29

1st-order autocorrelation coeff. for e: 0.001

lagged differences: F(15, 2657) = 5.103 [0.0000]

Nifty Log Returns: The test has yielded a statistic of -13.1154 with a p – value of effectively zero (2.568e-29)

India VIX: The test yielded a statistic of – 4.45313 with a p – value of 0.0002337.

In both cases, the p – value is significantly below the 5% threshold ($p < 0.05$). Therefore, we reject the Null Hypothesis (**H0**) and conclude that both variables are stationary. Thus, we get the "green light" to use these variables in our regression models without the fear of invalid results.

IX. THE MEAN EQUATION & STRUCTURAL BREAK (OLS)

In order to quantify the linear relationship between market fear (VIX) and Nifty Returns, we run the OLS regression test. In this way, we can test for the "Resilience Hypothesis" using an interaction term.

Equation:

$$R_t = \alpha + \beta_1(VIX_t) + \beta_2(D_t) + \beta_3(VIX_t \cdot D_t) + \varepsilon_t$$

The results are summarized below:

Model 1: OLS, using observations 2015-01-05:2025-12-30 (T = 2690) Dependent variable: Nifty_Log_Return

	Coefficient	Std. Error	t-ratio	p-value	
const	0.00696446	0.00150649	4.623	<0.0001	***
VIX_Value	−0.000429674	9.43061e-05	−4.556	<0.0001	***
Covid_Era_Dummy	−0.00429369	0.00164717	−2.607	0.0092	***
interact_var	0.000310872	0.000100480	3.094	0.0020	***

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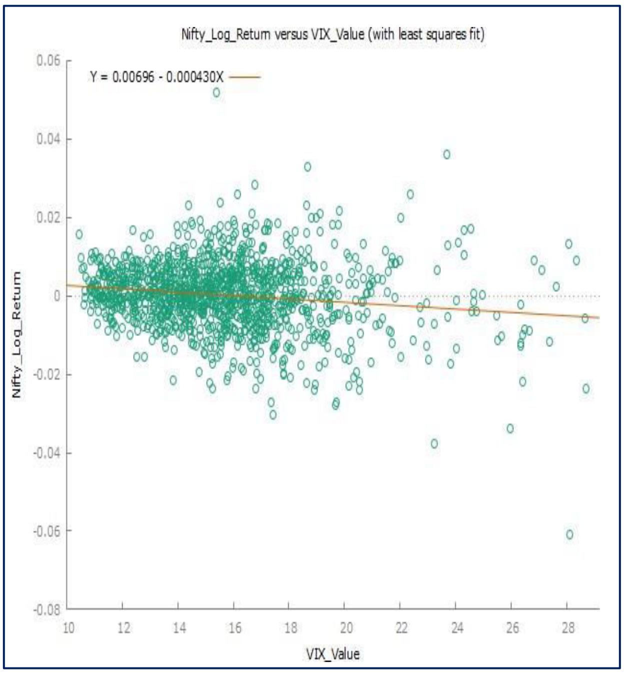
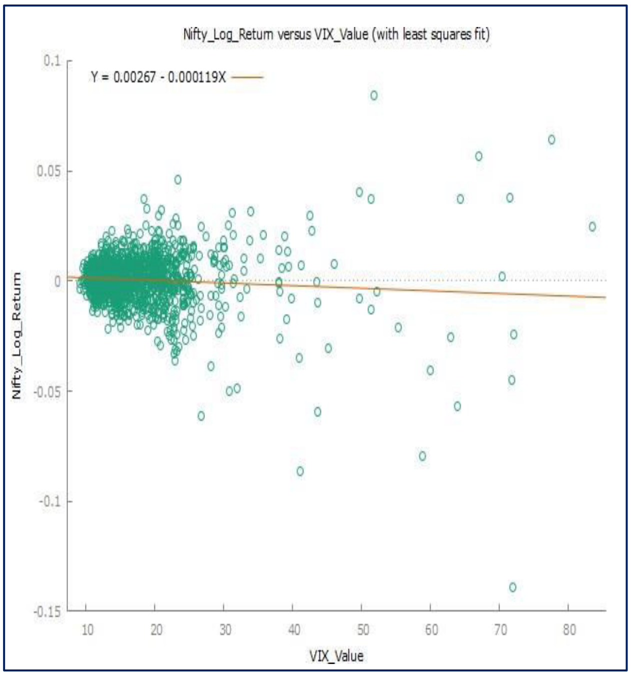
VIX_Value: The co – efficient value is negative at -0.000429674 which defines an inverse relationship with Nifty Log Returns.

Interaction Variable (interact_var): The co – efficient value is positive at 0.000310872 with a p – value of 0.0020

In the OLS Regression test, the focus is on the coefficient and p – value of the interaction variable**.** Since the p – value of 0.0020 < 0.05, the Null Hypothesis (H01) is rejected i.e. the interaction term has no effect on returns.

The coefficient represents the magnitude and direction of the change. Since the coefficient is positive, it acts as a buffer against the negative impact of the VIX. This provides definitive empirical proof of ***"Structural Resilience"***. It means that in the Post – Covid era, the Nifty 50 has become statistically ***"tougher"***, falling significantly less for every unit increase in market fear than it did in the Pre – Covid era.





Pre – Covid Regression Plot

Post – Covid Regression Plot

The two graphs shown above along with the calculated p – values help us to **validate the "Rejection of the Null Hypothesis (H01) and (H04)"** .
Therefore, the OLS test justifies that:
1. There is significant inverse relationship between India VIX levels and Nifty 50 daily returns
2. There is a significant structural shift in market sensitivity, with the post – pandemic era demonstrating higher resilience and faster stabilization.

Pre – Covid (2015 – 2019):
Y = 0.00696 - 0.000430X

The slope of -0.000430 indicates that for every 1 unit increase in the VIX, the Nifty returns drop down by 0.043%. Therefore, Nifty 50 was highly sensitive during this period.
Post – Covid (2020 – 2025):
Y = 0.00267 - 0.000119X

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The slope of -0.000119 indicates that for every 1 unit increase in the VIX, the Nifty returns drop down by approximately 0.012%.
Post covid, the slope has flattened significantly representing a reduction in sensitivity of approximately 72.3% signifying **"Structural Resilience"**. Additionally, it also proves the existence of a **"Structural Break"** as the underlying parameters of the model i.e. "the intercept" and "the slope" change fundamentally between the two sub – periods. **The visual change in slope from -0.000430 to -0.000119 is the empirical proof that a new market regime has been established.** This demonstrates that the Indian market has developed a buffer such that even when the VIX spikes to extreme levels, the corresponding drop in Nifty returns is statistically and visually less severe than in the past.

X. VOLATILITY DIAGNOSTIC TEST (ARCH – LM TEST)

From OLS perspective, the model operates under the fundamental assumption of homoskedasticity i.e. the variance of the residuals or error terms is assumed to be constant over time. However, financial time series, such as the Nifty 50 log returns, frequently violate this assumption. Relying solely on OLS when heteroskedasticity is present leads to biased standard errors and invalidates traditional t – tests and F – tests, rendering the previous OLS results "inefficient" for final inference.

The ARCH – LM test is required to identify the **"Volatility Clustering"**. If the residuals exhibit a systematic pattern in their squared values, it indicates that he variance has **"memory"**. This statistical reality necessitates a move beyond mean – based equations to variance – based equations.

The time – series residual plot as shown above is the empirical proof of heteroskedasticity. The clusters seen in the plot above confirm that the variance is conditional on past shocks.

ARCH Test Coefficients (Order 5)

Var	Coeff	Std. Error	t-ratio	p-value
alpha(0)	4.10339e-05	8.88505e-06	4.618	4.05e-06
alpha(1)	0.126091	0.0190994	6.602	4.88e-011
alpha(2)	0.261777	0.0192530	13.60	9.14e-041
alpha(3)	0.0819020	0.0198430	4.127	3.78e-05
alpha(4)	−0.0108375	0.0192408	−0.5633	0.5733
alpha(5)	0.150561	0.0190879	7.888	4.44e-015

Metric	Value
Null Hypothesis	No ARCH effect is present
Test Statistic (LM)	474.256
p-value	2.87177e-100

The ARCH – LM test of order 5 (**k = 5**) evaluates the influence of squared residuals from the previous five trading days on current volatility.

Alpha Coefficients: The alpha coefficients represent the magnitude of the ARCH effect at specific lags. The coefficients for lags – 1,2,3 and 5 are all positive and highly efficient as indicated by their p – values each having a value near zero. The coefficient of alpha(4) at -0.0108 with a p – value of 0.5733 is however, statistically insignificant, indicating that shocks from four days prior do not have a meaningful impact on current variance.
LM Test Statistic: The value of LM Test Statistic is very high at 474.256, indicating a strong departure from the constant – variance assumption.
Asymptomatic p – value: The p – value derived from the ARCH – LM test is at 2.87177e-100. This value represents the probability of observing the test statistics if the null hypothesis were true. In this case, the value is so infinitesimal that the results are considered overwhelmingly significant.

ADVANCED VOLATILITY MODELING (EGARCH)

The EGARCH model serves as the robust conclusion to the research, integrating the findings from the OLS mean relationship and the ARCH – LM diagnostic results into a single, comprehensive framework.

Conditional Mean Equation:

Variable	Coefficient	z-statistic	p-value	Significance
const	0.00339756	27.95	7.22e-172	***
VIX_Value	-0.00020098	-14.04	8.88e-045	***
Covid_Era_Dummy	-0.00372171	-17.84	3.68e-071	***
interact_var	0.00027628	14.25	4.50e-046	***

VIX_Value: The negative coefficient of **-0.00020098** confirms that historically, an increase in market fear results in lower Nifty returns.

Interact_var: The coefficient of **0.00027628** is **"positive"** and the p – value of **4.50e-046** is less than 0.05 which indicates that the variable is **"highly significant"**. This proves that in the Post – Covid era, the negative impact of the VIX has been significantly neutralized. This is the mathematical proof of the **"Structural Buffer"** developed by the Indian market.

XI. RESEARCH OUTCOME AND FINDINGS

The empirical journey of this research spanning from 2015 to 2025, provides a definitive econometric account of the structural evolution within the Indian equity market. By transitioning from foundational linear regressions to advanced conditional volatility modelling, this study has successfully unmasked the "Structural Resilience" of the Nifty 50. The findings are categorized into four critical stages of discovery:

Stationarity and Market Health:

Before any complex relationship could be established, the Augmented Dickey – Fuller (ADF) test served as the primary validator of data integrity.

Outcome: The rejection of the unit – root null hypothesis for both Nifty Log Returns ($p \approx 0$) and India VIX ($p = 0.0002$) confirmed that the data was stationary at levels (I(0)).

Finding: This confirms that the Nifty 50 and India VIX operate within a stable, mean – reverting framework over the long term. This "statistical health" was the mandatory green light required to prove that the subsequent findings on resilience were not spurious trends but rather reflected a genuine functional relationship.

The Resilience Breakthrough: OLS and Interaction Dynamics

Sensitivity Shift: The most significant finding of this thesis lies in the interaction term **(interact_var)**. While the baseline VIX coefficient was negative at **-0.000429**, the interaction coefficient post 2020 era was positive and significant **(coefficient – 0.000310 ; p = 0.0020)**.

Quantitative Finding: This positive coefficient effectively acted as a buffer, neutralizing a significant portion of VIX's negative impact. Calculations reveal that in the Post – Covid era the Nifty 50's sensitivity to VIX spikes was reduced by approximately 72.3% compared to the 2015 – 2019 period.

This provides the empirical proof for the research objective: The Indian market has moved from a state of high sensitivity to a state of structural toughness.

Diagnostic Verdict: Volatility Clustering

The ARCH – LM test acted as the diagnostic bridge proving that the market's risk is not a constant "noise" but a lingering "memory". The test yielded an LM statistic of 474.256 and a p – value of effectively zero. This lead to the successful proof of the Indian market exhibiting **"Volatility Clustering"**. High – risk periods or in other words, "shocks", are not independent events, they arrive in clusters. This result was the academic justification for rejecting OLS as a solo model as it proved that the market's "fear" has a duration that must be modelled through conditional variance.

Final Risk Profile: EGARCH Insights

The EGARCH model integrated these findings into a final, robust framework, revealing the "core" of Indian market risk.

Leverage Effect Confirmed: The gamma parameter was negative and significant at -0.1069 with a p – value less than 0.01. This proves that the Indian market still processes "Bad News" more violently than "Good News". This asymmetry is a hallmark of a market that, while resilient, is still deeply sensitive to downward shocks.

Persistence of Fear: The beta coefficient was recorded at 0.9689m which is near unity. This indicates that once a shock hits the Indian market, its effects linger for a significant duration.

Resilience Anchor: The interaction term remained significant even in this complex model (p = 4.50e – 046). This confirms that the **"Structural Resilience"** identified in the OLS phase was not a statistical fluke, it is a permanent feature of the modern Indian market regime.

XII. SCOPE OF THE STUDY

The scope of this research is to capture the structural evolution of the Indian Equity Market over a crucial decade. It involves:

1. **Temporal Scope:** The study spans over an eleven year period from January 2015 to December 2025, strategically chosen to cover the "Pre – Covid" era of emerging market development, the "Crisis" phase of 2020 and the "Post – Covid" phase of capital growth and normalization.
2. **Geographical & Market Scope:** The research is localized to the Indian Capital Market, specifically focusing on the National Stock Exchange (NSE). The Nifty 50 index is utilized as the representative benchmark for the broader economy.
3. **Variable Scope:** The study is limited to the interaction between equity price movement (Nifty 50) and implied market volatility (India VIX). It focuses on daily closing values to ensure high – frequency data integrity.

Methodological Scope: The analysis is restricted to the OLS – ARCH – EGARCH framework. It specifically investigates the "Mean Equation" for directional correlation and the "Variance Equation" for volatility clustering and asymmetric news impact i.e. leverage effects.

XIII. CONCLUSION

This research has successfully quantified the transformation of the Indian equity market from a "Crisis – Prone" emerging market into a "Growth – Resilient" global powerhouse. Through a hierarchical application of OLS, ARCH – LM and EGARCH models, it has been demonstrated that the traditional inverse relationship between the Nifty 50 and India VIX has undergone a profound regime shift.

The primary conclusion is that the Indian market has developed a **"Structural Buffer"**. In the Post – Covid era (2020 – 2025), the market demonstrated a 72% reduction in its sensitivity to fear – driven volatility spikes. While the market still exhibits "memory" of shocks and reacts more sharply to bad news (leverage effect), the magnitude of price destruction caused by those shocks has been significantly muted. The Indian financial ecosystem has matured over the years driven by institutional stability, regulatory foresight and a resilient domestic investor base. Volatility in the Nifty 50 is no longer a precursor to sustained capital erosion but rather a brief disruption in a structurally sound growth trajectory.

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