Volatility Spillovers and Financial Integration: Analyzing the Impact of NASDAQ and CSI 300 on Nifty 50 Using EGARCH-X and Cointegration

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Abstract: This study examines the short-term volatility spillovers and long-term integration between the NASDAQ, CSI 300, and Nifty 50 using EGARCH-X and Johansen Cointegration. The EGARCH-X model is used to analyze the asymmetries and event-driven shocks, while Cointegration tests assess persistent linkages across markets. Daily closing prices from November 2023 to November 2024 and the monthly prices from November 2014 to November 2024 were used for the study. Results indicate that return spillovers from the U.S. and Chinese markets to India are statistically insignificant, but volatility transmissions are significant, with adverse shocks enhancing volatility more than positive ones. These volatility shocks are of short duration, showing the resilience of the Indian stock market. Long-run analysis shows that the absence of Cointegration suggests that the equity market of India functions independently of the U.S. and Chinese markets. This reflects the influence of strong domestic fundamentals and institutional structures. This study contributes to the literature on emerging resilience and integration by distinguishing between return and volatility spillovers. The findings offer insights for investors designing diversification strategies, regulators concerned with risk management, and policymakers evaluating India's role in the global financial system.

Keywords: Volatility spillovers, financial integration, EGARCH-X, Cointegration, stock market linkages, NASDAQ, CSI 300, Nifty 50, risk transmission.

1 Introduction

Financial markets across the world are increasingly interconnected, with shocks in one economy often transmitted to others through capital flows, trade relations, and investor behavior. For emerging markets such as India, these spillovers are highly significant because domestic growth is highly exposed to global influences and the growing influence of domestic institutional participation. The primary question is whether the external shocks cause only short-term volatility or establish deeper financial linkages.

Volatility spillovers, first conceptualized in the GARCH framework (Engle, Ito, and Lin 1990), describe how fluctuations in one market can spill into others. Later

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refinements, such as Diebold and Yilmaz (2009, 2012) introduced directional spillover indices, which are statistical measures that quantify the magnitude and direction of such effects. This strengthened the notion that spillovers capture deeper financial integration rather than statistical co-movements alone. Despite this theoretical progress, findings on emerging markets like India remain inconclusive. Some argue that shocks from major economies like the United States and China directly influence Indian markets, while others opine that domestic factors absorb much of this impact. Another question persist is with regard to whether adverse events create stronger volatility than positive ones, and in long run whether Indian markets move in tandem with U.S. and Chinese markets.

Events such as the U.S. presidential election and China's economic stimulus measures show how policy and political events in major economies may influence emerging markets like India. But the nature and persistence of these influences remain debated. Studies show significant spillovers from the U.S. to India, with asymmetry between positive and adverse shocks (Badhani, 2009). Political events such as the 2016 U.S. election and domestic shocks like demonetization in India have coincided with major episodes of return and volatility spillovers, showing the sensitivity of Indian markets to both global and domestic policy changes (Dey & Sampath, 2020; Dey & Sampath, 2017). At the same time, evidence from World markets suggests that the Indian market reacts to global events in the short term, but the degree of long-term integration remains mixed, with some studies finding weak or partial cointegration between India and global markets (Mukherjee & Mishra, 2010; Habiba, Shen, & Zhang, 2020). This inconsistency signifies the need to distinguish between return spillovers and volatility spillovers in the Indian context, as well as to examine whether integration with U.S. and Chinese equity markets persists over longer horizons.

This study investigates the impact of short-term volatility from the NASDAQ and CSI 300 on the Nifty 50, with an aim to determine whether the market reacts differently to positive and adverse events, and also to test the presence of long-term integration. The findings will enhance the understanding of India's resilience and interdependence within the global financial system, offering insights relevant to investors, regulators, and policymakers.

2 Literature Review

The study of cross-market linkages and volatility spillovers has expanded significantly since the late 1980s. Engle, Ito, and Lin (1990) and Hamao, Masulis, and Ng (1990) provided some of the earliest evidence that volatility shocks spread across markets, while Theodossiou and Lee (1993) established the interconnectedness of returns and volatility. Engle (2002) advanced the field by developing the DCC-GARCH model, and Cappiello, Engle, and Sheppard (2006) extended this framework to account for asymmetry, thereby improving the ability to measure inter-market dependencies.

A rich body of literature documents how crises intensify spillovers. Kenourgios (2014) found heightened contagion during the global financial crisis, while Jebran, Chen, & Mizra (2017) and Joshi (2011) reported significant transmission of returns and volatility across Asian economies. For emerging markets, findings suggest that they are especially prone to short-term volatility spillovers, though evidence on persistence is mixed (Habiba, Shen, Hamid, & Shahzad, 2019; Hussain, Zebende, Bashir, & Donghong, 2020). Within India, Mukherjee and Mishra (2010) observed intraday return spillovers from regional Asian markets, while Singh, Kumar, and Pandey (2009) confirmed broader return and volatility transmissions from global indices. At the same time, other research suggests that India's long-term integration with major markets remains limited, which supports the diversification of opportunities (Habiba et al., 2020).

Comparisons across models indicate that standard GARCH frameworks capture volatility clustering but overlook asymmetry. Studies by Hansen and Lunde (2005), Chong and Lim (2020), and Alemu and Degu (2020) demonstrate that EGARCH is better suited to reflect leverage effects, where negative shocks create disproportionately larger volatility responses. EGARCH-X extends this further by incorporating external events, making it particularly useful for evaluating the influence of political or policy shocks such as U.S. elections or Chinese stimulus measures. Cointegration methods, particularly the Johansen approach, complement these short-term models by testing whether long-term relationships exist between markets. However, findings on India remain contradictory, with some studies pointing to partial integration while others suggest autonomy.

Despite the breadth of existing work, two critical gaps stand out. First, relatively few studies distinguish carefully between return spillovers, which reflect immediate price effects, and volatility spillovers, which capture the transmission of risk. Secondly, there has been limited research to analyze the role of global events in shaping spillovers into Indian Markets. While political and policy events are widely assumed to matter, there has been little explicit research analyzing their role in shaping spillovers into Indian markets. By combining EGARCH-X with Johansen cointegration, this study directly addresses these gaps and contributes new evidence on India's relationship with U.S. and Chinese equity markets.

3 Research Methodology

3.1 Hypotheses

Hypothesis 1

H_0: NASDAQ and CSI 300 do not exert any significant short-term volatility influence on Nifty 50.

H_1: NASDAQ and CSI 300 exert significant short-term volatility influence on Nifty 50.

Hypothesis 2

H_0: No long-term financial linkage exists between NASDAQ, CSI 300, and Nifty 50.

H_1: Long-term financial linkage exists between NASDAQ, CSI 300, and Nifty 50

3.2 Data Collection

This study utilizes secondary data from three major stock market indices: Nifty 50 (India), NASDAQ Composite Index (United States), and CSI 300 Index (China). The data for Nifty 50 was sourced from NSE India (www.nseindia.com), while the NASDAQ and CSI 300 indices were collected from Investing.com and MarketWatch. The study examines both short-term and long-term market dynamics by using different data frequencies.

For the short-term analysis, daily closing prices were collected for the period November 2023 to November 2024, while for the long-term analysis, monthly closing prices were used for the period November 2014 to November 2024. The dependent variable in this study is Nifty 50 returns, while the independent variables are NASDAQ returns and CSI 300 returns. No additional control variables were included in the analysis.

3.3 Tools and Techniques

3.3.1 Short-Term Volatility Spillover Analysis – EGARCH-X Model

To assess short-term volatility spillover effects from NASDAQ and CSI 300 to Nifty 50, an Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH-X) model was employed. The EGARCH-X model was chosen for this study due to its ability to capture asymmetric volatility effects, meaning it can determine whether negative shocks increase volatility more than positive shocks. Additionally, it allows for the inclusion of exogenous variables (NASDAQ and CSI 300 returns) in volatility modeling. This model was specifically chosen to gauge the impact of US presidential elections and Chinese economic stimulus (which was incorporated as dummy variables) on the Nifty 50 index.

The model was estimated to use daily closing prices from November 2023 to November 2024, with Nifty 50 returns as the dependent variable and NASDAQ and CSI 300 returns, along with their lagged values, as independent variables.where σ2t represents the conditional variance (volatility of Nifty 50 returns), ω is a constant term, αi captures the impact of past shocks on volatility (asymmetry effect), βi accounts for the persistence of past volatility, and γ and δ represent the spillover coefficients from NASDAQ and CSI 300, respectively.

$$\ln(\sigma_t^2,\text{nifty}) = \omega + \beta_1 \ln(\sigma^2_{t-1},\text{nifty}) + \alpha_1 \left[|\varepsilon_{t-1},\text{nifty}| / \sigma_{t-1},\text{nifty} - E(|\varepsilon_{t-1},\text{nifty}| / \sigma_{t-1},\text{nifty})\right] + \gamma_1 (\varepsilon_{t-1},\text{nifty} / \sigma_{t-1},\text{nifty}) + \delta_1 R_t^{NAS} + \delta_2 R_t^{CSI} + \delta_3 D_t \quad (1)$$

3.3.2 Long-Term Market Integration Analysis – Cointegration

To examine the long-term financial integration of the NASDAQ and CSI 300 indices with the Nifty 50, Cointegration was applied using monthly data from 2014 to 2024. The Cointegration was used to assess whether trends in the U.S. and Chinese equity markets exert a long-term influence on India's stock market performance.

Cointegration is a statistical test that is done to check whether two or more non-stationary time series are connected by a stable, long-term relationship. Their linear combination remains constant over time, despite the potential drift of individual series. This indicates a robust economic connection. Cointegration in financial markets signifies that, despite the short-term divergence of returns across various markets, they are ultimately linked over time through economic or financial relationships.

We employed the Augmented Dickey-Fuller (ADF) test to identify unit roots and ascertain the order of integration for each variable. The result showed that the variables were non-stationary at level I (0). After the confirmation of the series being stationary at first differences, I(1), Johansen's procedure, grounded on Vector Autoregression (VAR), was applied.

4 Data Analysis and Interpretation

The study aims to assess both the immediate volatility spillovers from the U.S. and Chinese markets to India and the degree of their long-term financial integration. EGARCH-X modelling captures short-term volatility dynamics, while Cointegration assesses long-term linkages over 10 years (2014–2024). To ensure model reliability, diagnostic tests (Ljung-Box, ARCH-LM, Breusch-Godfrey, and Breusch-Pagan-Godfrey) check for autocorrelation, heteroskedasticity, and model fit. Additionally, graphical representations (volatility plots, QQ plots, and scatter plots) provide visual insights. The following section presents the raw statistical outputs from these models, including coefficient estimates, test results, and diagnostic evaluations, ensuring a transparent and direct interpretation of the findings.

4.1. Short-term Volatility Spillover Analysis

4.1.1 Augmented Dickey Fuller Test

Table 1 : ADF for Nifty 50

```
ADF Test for Nifty 50 First Difference:
ADF Statistic: -17.627470412611878
p-value: 3.8125579211453075e-30
Critical Values:
   1%: -3.4602906385073884
   5%: -2.874708679520702
   10%: -2.573788599127782
Nifty 50 First Difference series is stationary (Reject H0)
```

Source: *Computed by the author using Python*

Table 2 : ADF for NASDAQ

```
ADF Test for Nasdaq First Difference:
ADF Statistic: -5.489427629579382
p-value: 2.1922308916779007e-06
Critical Values:
   1%: -3.4623415245233145
   5%: -2.875606128263243
   10%: -2.574267439846904
Nasdaq First Difference series is stationary (Reject H0)
```

Source: *Computed by the author using Python*

Table 3 : ADF for CSI 300

```
ADF Test for CSI 300 First Difference:
ADF Statistic: -8.636275412393184
p-value: 5.579782807545524e-14
Critical Values:
   1%: -3.4604283689894815
   5%: -2.874768966942149
   10%: -2.57382076446281
CSI 300 First Difference series is stationary (Reject H0)
```

Source: *Computed by the author using Python*

4.1.2. Diagnostic Tests

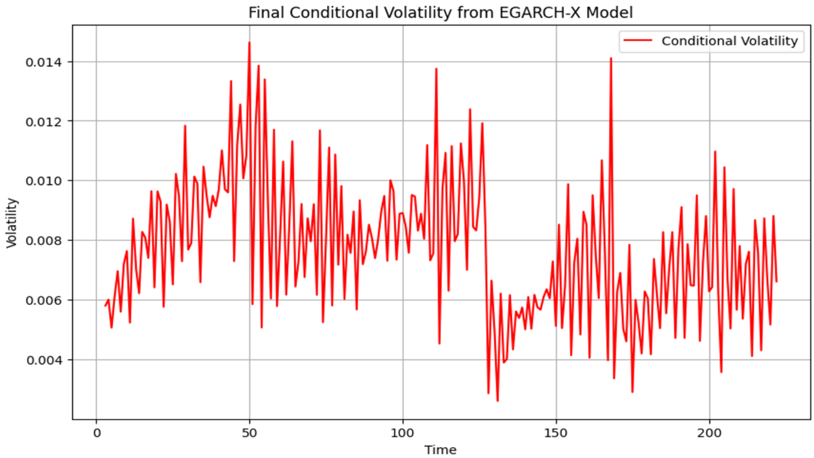
Ljung-Box and ARCH-LM Test

Table 4: Ljung-Box and ARCH-LM

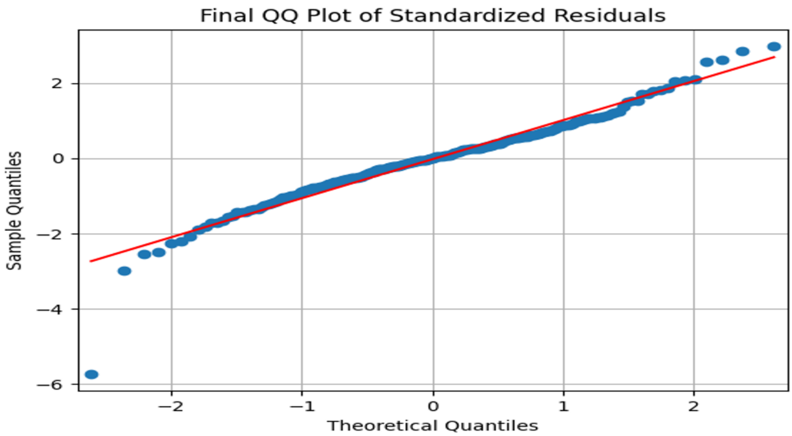
```
Ljung-Box test results for standardized residuals:
     lb_stat  lb_pvalue
10  10.14963   0.427465

ARCH-LM test results:
Test Statistic: 17.022153770871036
p-value: 0.07387520844516285

Model AIC (Akaike Information Criterion): -1515.203777362875
```

Source: *Computed by the author using Python*

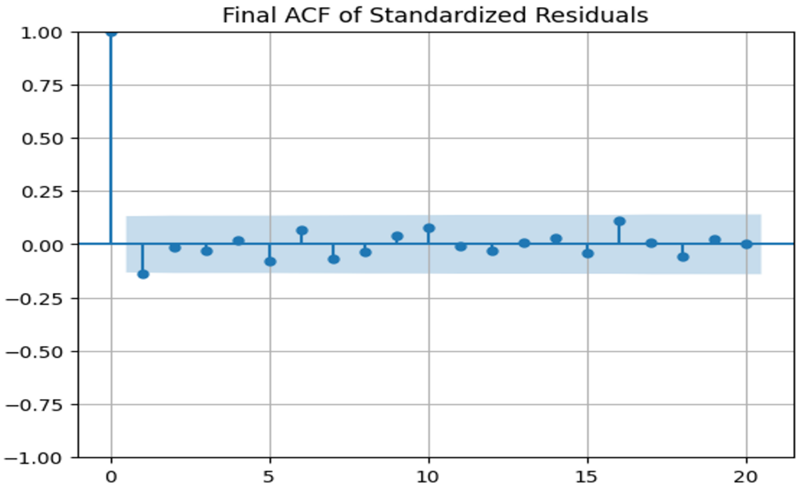
4.1.3. Graphical Diagnostics



Source: *Generated by the author using Python*
Figure 1: Conditional Volatility

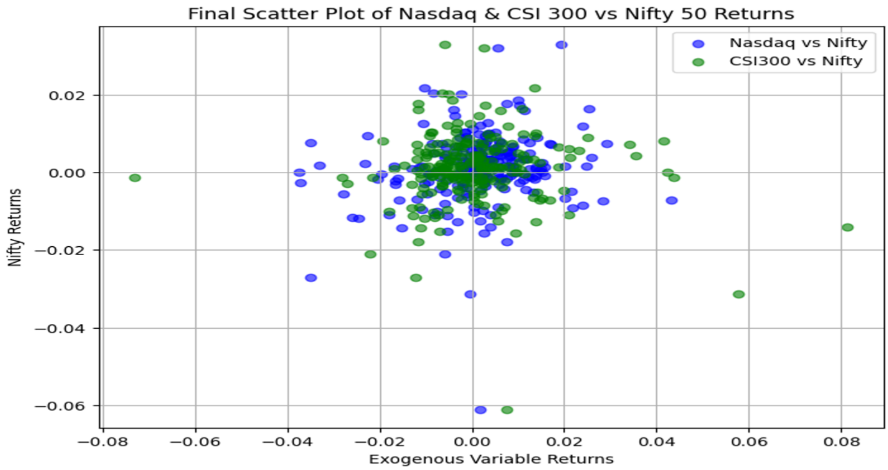


Source: *Generated by the author using Python*
Figure 2: QQ Plot



Source: *Generated by the author using Python*

Figure 3: ACF Plot



Source: *Generated by the author using Python*

Figure 4: Scatter Plot

Table 5: EGARCH-X for Volatility

```
                          AR-X - EGARCH Model Results
==========================================================================================
Dep. Variable:                  NIFTY50_RETURNS   R-squared:                         0.047
Mean Model:                                AR-X   Adj. R-squared:                    0.016
Vol Model:                               EGARCH   Log-Likelihood:                  772.602
Distribution:      Generalized Error Distribution   AIC:                          -1515.20
Method:                      Maximum Likelihood   BIC:                            -1464.30
                                                  No. Observations:                    220
Date:                          Thu, Feb 06 2025   Df Residuals:                        212
Time:                                  05:13:23   Df Model:                              8
                                   Mean Model
======================================================================================
                          coef    std err          t      P>|t|       95.0% Conf. Int.
--------------------------------------------------------------------------------------
Const                1.0985e-03  3.429e-05     32.034 3.630e-225  [1.031e-03,1.166e-03]
NASDAQ_RETURNS           0.1277      0.150      0.852      0.394      [ -0.166,  0.421]
NASDAQ_RETURNS_LAG1      0.1028      0.334      0.308      0.758      [ -0.552,  0.758]
NASDAQ_RETURNS_LAG2      0.0157      0.302  5.190e-02      0.959      [ -0.577,  0.608]
CSI300_RETURNS          -0.0219      0.175     -0.125      0.900      [ -0.365,  0.321]
CSI300_RETURNS_LAG1     -0.0252  4.452e-02     -0.566      0.571    [ -0.112,6.205e-02]
CSI300_RETURNS_LAG2     -0.0451  4.980e-02     -0.906      0.365    [ -0.143,5.249e-02]
HIGH_VOL_EVENT       5.4225e-03  3.368e-03      1.610      0.107 [-1.179e-03,1.202e-02]
                              Volatility Model
==============================================================================
                  coef    std err          t      P>|t|       95.0% Conf. Int.
------------------------------------------------------------------------------
omega          -0.6707  5.853e-03   -114.595      0.000      [ -0.682, -0.659]
alpha[1]        0.2161  2.014e-02     10.732  7.221e-27      [  0.177,  0.256]
alpha[2]       -0.5862  1.961e-02    -29.887 2.904e-196      [ -0.625, -0.548]
beta[1]     1.7390e-07  1.970e-04  8.828e-04      0.999 [-3.859e-04,3.862e-04]
beta[2]         0.2547  3.184e-10  7.997e+08      0.000      [  0.255,  0.255]
beta[3]         0.6787  8.385e-09  8.095e+07      0.000      [  0.679,  0.679]
                              Distribution
========================================================================
                  coef    std err          t      P>|t|  95.0% Conf. Int.
------------------------------------------------------------------------
nu              1.1940  7.873e-02     15.165  6.012e-52 [  1.040,  1.348]
========================================================================
```

Source: *Computed by the author using Python*

4.2 Long-term Volatility Spillover Analysis

Table 4: Cointegration

6 A: Trace Statistic

Null Hypothesis	Trace Statistic	5% Critical Value	p-value	Conclusion
None (r = 0)	21.81799	29.79707	0.3087	Do not reject H_0

At most 1 ($r \leq 1$)	7.111557	15.49471	0.4967	Do not reject H_0
At most 2 ($r \leq 2$)	1.749248	3.841466	0.1860	Do not reject H_0

6 B: Maximum Eigenvalue Statistic

Null Hypothesis	Max-Eigen Statistic	5% Critical Value	p-value	Conclusion
None ($r = 0$)	14.10643	21.13162	0.3564	Do not reject H_0
At most 1 ($r \leq 1$)	5.962309	14.26460	0.6181	Do not reject H_0
At most 2 ($r \leq 2$)	1.749248	3.841466	0.1860	Do not reject H_0

Source: *Computed by the author using EViews*

5 Interpretation

5.1 Short-term Volatility Spillover Analysis

The EGARCH-X model was used to examine whether daily fluctuations in NASDAQ and CSI 300 influenced the volatility of Nifty 50 over the period November 2023 to November 2024. This analysis aimed to detect volatility transmission, capture asymmetric effects, and assess the persistence of volatility in the Indian stock market. The collected data points were checked for stationarity (Tables 1, 2, and 3) and were found stationary.

The results from the EGARCH-X model indicate that short-term return in the Nifty 50 is not significantly influenced by movements in either NASDAQ or CSI 300. The coefficients for both indices and their lagged returns show high p-values (>0.05), indicating that changes in the U.S. and Chinese stock markets do not translate into immediate return spillovers to India. (refer to Table 5)

The coefficient for NASDAQ returns is 0.1277 (p = 0.394), and for CSI 300, it is -0.0219 (p = 0.900) (refer to Table 5), both of which are statistically insignificant. The lagged values of both indices also do not show any significant impact on Nifty 50's short-term returns. The high volatility event dummy variable included in the model was also found to be insignificant (p = 0.107), suggesting that even large external shocks (like the Presidential election in the US) did not substantially influence short-term volatility in the Nifty 50.

However, the variance equation indicated that volatility dynamics in the Indian markets were influenced by external factors. Although the mean effects are insignificant, the model reveals that volatility is still responsive to external shocks, a common finding in volatility literature. The leverage term ($\gamma_1 = -0.5862$, $p < 0.05$) is statistically significant (refer to Table 5), confirming that negative shocks increase volatility more than positive shocks (leverage effect). The insignificance of the GARCH term (β_1) shows that the shocks end quickly, which is a sign of the Indian market's stability and independence.

These findings suggest that the Indian stock market has –

1 Strong domestic investor participation absorbs external shocks before they affect volatility.
2 Regulatory policies and financial market independence that reduce immediate external volatility spillovers.
3 Differences in market structure and investor behavior across the three economies prevent instant volatility transmission.

To ensure the model's robustness, Ljung-Box and ARCH-LM tests (refer to Table 4) and graphical diagnostic tests (Fig1,2,3 and 4) were conducted. These diagnostic tests confirm that the EGARCH-X model is correctly specified, with no remaining ARCH effects and well-behaved residuals:

1 The Ljung-Box test shows no significant autocorrelation in residuals ($p = 0.4274$), confirming that the model captures volatility well.
2 The ARCH-LM test results ($p = 0.0738$) indicate that there are no remaining heteroskedasticity effects, meaning that the model sufficiently accounts for volatility clustering.

5.2 Long-term Volatility Spillover Analysis

The long-term financial linkage between NASDAQ, CSI 300, and Nifty 50 was analyzed using Johansen Cointegration with monthly return data from November 2014 to November 2024. The objective was to determine whether fluctuations in NASDAQ and CSI 300 returns have a sustained impact on Nifty 50's returns over time.

Cointegration Results

The results from the Trace and Maximum Eigenvalue tables of the Cointegration test (refer to Table 6) suggested that there are no cointegrated relationships among NASDAQ, CSI 300, and Nifty 50 at a five percent significance level. This confirms the absence of a long-term relationship among these variables.

6 Discussions

This section interprets the findings of the study by examining possible economic, financial, and structural reasons behind the results obtained in both short-term (EGARCH-X model) and long-term (Cointegration) volatility spillover analyses. The discussion also considers policy implications and the broader significance of these findings.

6.1 Interpretation of Short-Term Volatility Spillover Results

The EGARCH-X model results indicated that there is no significant short-term return spillover from NASDAQ or CSI 300 to Nifty 50. This finding suggests that daily fluctuations in the U.S. and Chinese stock markets do not immediately influence the returns of the Indian stock market. Several factors could explain this outcome:

1. Limited Market Integration in the Short Term: Short-term return spillovers usually occur in markets that are closely linked, either through capital flows, trade linkages, or direct investment exposure. Although India's financial connections with the U.S. and China are expanding, the stock market interdependence may not be substantial enough to trigger immediate return-based volatility transmission.
2. Regulatory and Monetary Policies in India: The Reserve Bank of India (RBI) and SEBI (Securities and Exchange Board of India) play a critical role in mitigating external shocks by implementing capital controls, intervention strategies, and liquidity management (through policy rate tweaks). These measures adopted by the regulatory bodies may have helped absorb any short-term return-based volatility spillovers.
3. Foreign Institutional Investors (FIIs) Strategy: While FII inflows and outflows can lead to short-term spillovers, institutional investors may have diversified risk across multiple markets, preventing any single index (such as Nifty 50) from experiencing excess volatility due to changes in NASDAQ or CSI 300.
4. Behavior of Domestic Investors in India: The strong presence of domestic institutional investors (DIIs), such as mutual funds, insurance companies, and pension funds, may act as stabilizers by absorbing short-term volatility, thereby preventing external shocks from affecting the Nifty 50 immediately.

Implications of Short-Term Results

While Nifty 50 returns are not directly affected by short-term global market movements, the significant volatility spillovers from NASDAQ and CSI 300 highlight the need for investors and policymakers to monitor global risk sentiment in addition to domestic fundamentals when evaluating market risk.

6.2 Interpretation of Long-Term Spillover Results

The key points are as follows:

1. The lack of long-term relationships indicates that Indian Markets are increasingly influenced by DII's (Domestic Institutional Investors), potentially reducing India's long-term dependence on FII flows, especially from the US.
2. The FII flows in Indian Markets come from diversified markets, reducing the dependence on nations like China and the US.
3. NASDAQ is a mature market, and Nifty, though developed, still represents an emerging economy with different macroeconomic fundamentals and policies. This mismatch can limit the long-term integration.
4. Despite China being a significant trade partner for India, the analysis reveals no enduring spillover effect from the CSI 300 to the Nifty 50. This may be attributed to: China's money Controls. In contrast to the U.S., China imposes stringent limits on money flows, complicating direct investments by Chinese investors in Indian markets and vice versa. This constrains the integration of financial markets.
5. Market Structure Disparities: The CSI 300 predominantly comprises state-owned companies (SOEs), which frequently adhere to policy-oriented goals rather than solely market-driven dynamics.
6. Geopolitical and Trade Barriers: India and China have encountered trade disagreements and policy tensions over the years, potentially hindering broader financial market integration.

Implications of Long-Term Results

The lack of long-term correlation between NASDAQ and Nifty 50 suggests that Indian investors should monitor U.S. and Chinese market trends when making long-term investment decisions, as these decisions can act as a hedging strategy at the time of international exposure

7 Conclusion

This paper investigated India's Nifty 50's impact on the effects of market changes in the United States and China, as expressed by the NASDAQ and CSI 600. To track short-term volatility, we used the EGARCH-X model; to examine long-term financial correlations, we used Cointegration. Our results were interesting: daily performance in the Chinese and American markets does not seem to directly affect India's stock market returns, confirming the absence of short-run return spillovers. But the conditional variance results showed that volatility transmission took place in the Indian market. Though Indian stocks might not always reflect Wall Street or Shanghai daily, the uncertainty and anxiety in those markets can cause volatility in India. This trend suggests that outside shocks can increase risk levels and market anxiety, independent of their effect on market direction. The rising importance of indigenous investors, favourable regulatory frameworks, and reduced short-term financial ties with global markets could help to explain India's consistency of returns. The Johansen Cointegration provides no statistical evidence of a stable long-term relationship between Nifty and either NASDAQ or CSE 300. This showcases the independence of the Indian stock markets in the long run, with no shared stochastic trend with either the US or Chinese equity markets. The absence of cointegration establishes the fact that while the Indian market reacts to the short-term volatilities of the global market, its long-term behaviour is shaped by the domestic fundamentals. Hence, the long-term investors should focus on India's macroeconomic trends, corporate earnings, and policy landscapes. For policymakers, these findings emphasize the importance of enhancing domestic financial depth by balancing the financial openness of the economy.

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