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Do Global FinTech Innovations Influence Emerging Markets? Evidence from KFTX and Nifty 50

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Introduction

The financial sector has undergone a profound transformation since the advent of financial technology (FinTech), a term coined in 1990 that gained significant momentum in the late 2000s. Initially concentrated on backend operations of financial institutions, FinTech has evolved into a comprehensive ecosystem that encompasses banking, financial service providers, customers, startups, credit card agencies, and lending institutions. This technological revolution has fundamentally altered the landscape of the finance industry through innovative business models that prioritize both growth and sustainability (Zhang & Tong, 2023).

The integration of FinTech has emerged as a critical indicator of national development and quality of life, prompting countries worldwide to enhance their FinTech infrastructure. As Chen (2016) notes, FinTech serves as a vital link between traditional finance and real-world needs, transforming how financial services are delivered and consumed. This transformation has been particularly pronounced in emerging markets, where FinTech adoption enables higher wealth creation while exemplifying sustainable business practices and contributing to Sustainable Development Goals (Sunaryo & Leon, 2023).

The global distribution of FinTech firms reveals a concentrated presence in key financial hubs, with India positioned among the top 10 hotspots alongside the UK, US, Singapore, and UAE. The industry spans multiple domains, with Digital Banking & Services commanding the largest representation, followed by Digital Capital Raising, and the emerging WealthTech segment. Notably, 24% of worldwide FinTech firms generate revenues exceeding \$2 million, underscoring the sector's commercial viability and growth potential.

A robust financial system serves as a fundamental pillar for economic growth, and FinTech has demonstrated its capacity to enhance financial sector development by improving access to loans, depth of deposits, and magnitude of savings (Muganyi et al., 2022). This recognition has led nations to invest heavily in FinTech infrastructure, making it essential to understand the return on investment of such technological initiatives. Investment theories suggest that stock market indicators serve as reliable barometers of success, with established positive correlations between FinTech inclusion and corporate efficiency (Lv & Xiong, 2022).

While extensive research has examined FinTech's impact on national and corporate growth in markets such as China (Li & Wang, 2025), the United States (Guo et al., 2024), Russia, and Ukraine (Hasan et al., 2024), particularly focusing on financial sectors and banking institutions, the Indian market remains relatively underexplored in this context. The FinTech Index, with its proven predictive capability for surplus returns compared to conventional economic indicators, provides a valuable framework for such analysis (Guo et al., 2024).

Given the high degree of co-movement between Indian and global markets, examining how FinTech announcements at both global and Indian levels impact stock market performance becomes particularly relevant (Maheshwari & Kapoor, 2022). This study addresses this gap by investigating the relationship between global FinTech innovations and emerging market performance, specifically examining the influence of the KraneShares MSCI All China Index ETF (KFTX) as a proxy for global FinTech developments on India's Nifty 50 index.

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The research contributes to the growing body of literature on FinTech's market impact by focusing on cross-border spillover effects in emerging economies, providing insights into how rapidly and extensively FinTech-related information is absorbed across international markets. Understanding these dynamics is crucial for policymakers, investors, and financial institutions operating in the increasingly interconnected global FinTech ecosystem.

Literature Review

The existing literature reveals a fundamental shift in how FinTech adoption is perceived within financial ecosystems. Rather than serving as a competitive differentiator, FinTech adoption has evolved into what researchers characterize as a "hygiene factor" rather than a motivating factor (Marda & Sinha, 2022). This conceptual framework suggests that while FinTech adoption may not create sustainable competitive advantages, the absence of such adoption increasingly results in competitive disadvantages for financial institutions and corporations.

The literature demonstrates compelling evidence for the value-creating potential of FinTech integration at the corporate level. Companies engaging with FinTech through system improvements or mergers and acquisitions consistently exhibit superior financial performance. Dranev, Frolova, and Ochirova (2019) provide empirical evidence showing that companies demonstrated supernormal returns following the acquisition of FinTech firms, suggesting that markets positively value such strategic moves.

The anticipatory effects of FinTech investment are equally significant. Euchner and Goldenius (2019) found that companies announcing proposed investments in FinTech experience abnormal returns, indicating that market participants view such announcements as positive signals about future performance.

FinTech integration delivers tangible financial benefits beyond market valuation improvements. Zhang and Huang (2022) documented how FinTech inclusion enables Chinese companies listed on Shenzhen and Shanghai stock exchanges to reduce debt financing costs. This finding suggests that FinTech adoption enhances corporate creditworthiness and financial efficiency, leading to more favorable borrowing terms and improved capital structure management.

The banking sector represents a critical domain for examining FinTech's impact on market performance. Carlini, Del Gaudio, Porzio, and Previtali (2022) established that FinTech-inclusive banks consistently receive higher market valuations compared to traditional banks. This valuation premium reflects market confidence in the technological capabilities and future growth prospects of digitally transformed financial institutions. The comprehensive study by Khosravani and Bahman (2023) provides detailed evidence of FinTech's positive impact across multiple banking performance indicators. Their research demonstrated significant improvements in bank activity diversification, as measured by the Herfindahl-Hirschman Index, enhanced Loan to Asset Ratios, and more balanced Income Distribution Across Activities. These findings indicate that FinTech adoption enables banks to diversify their revenue streams while maintaining operational efficiency.

The literature reveals important insights into how FinTech adoption by individual firms affects broader market dynamics. Peltola (2021) conducted multivariate analysis examining the effects of FinTech mergers and acquisitions, discovering that while the direct effects on acquiring firms were limited, significant complementary effects emerged among industry peers. This finding suggests that FinTech adoption by one competitive firm creates ecosystem disruption, compelling others to pursue similar technological integration to maintain competitive parity.

Not all markets demonstrate positive FinTech effects, highlighting the importance of regional and institutional contexts. Asmarani and Wijaya (2020) conducted comprehensive analysis of Indonesian retail banks using the Fama-French Three-Factor Model and panel data regression for the period 2016-2018. Their findings revealed no significant effect of FinTech on retail bank stock returns, suggesting that FinTech's impact may vary significantly across different market maturity levels, regulatory environments, and institutional frameworks.

Stock exchanges themselves have become active participants in the FinTech ecosystem, with their technological adoption generating measurable market effects. The Istanbul stock market's experience with FinTech integration provides valuable insights into the short-term volatility patterns associated with technological transitions. Research utilizing GJR-GARCH-in-Mean and I-GARCH models revealed that the BISTECH transition initially increased market volatility significantly, creating disruptive effects on financial markets before stabilizing at improved efficiency levels.

Missaoui, Shah, and Ben Rejeb (2025) contributed important insights into FinTech's role during crisis periods through their analysis of African stock markets during COVID-19 and the Russian-Ukraine conflict. Their research identified significant spillover effects, with exchanges in Egypt, Kenya, Tanzania, and Johannesburg serving as primary transmitters of volatility spillovers, while Nigeria, Morocco, and Tunisia emerged as shock-receiving markets.

Research on FinTech's impact on financial stability in emerging markets has revealed complex relationships. Studies using data from 37 commercial banks in Vietnam for the period 2010–2020 found that FinTech development negatively affected financial stability, and market discipline can mitigate this effect. However, heterogeneity analysis showed that these effects vary significantly across different types of financial institutions and market conditions. These findings suggest that the relationship between FinTech innovations and emerging market stability is nuanced and context-dependent, with potential for both positive developmental effects and destabilizing influences.

The interconnected nature of global financial markets creates complex networks through which FinTech innovations can influence distant markets. Research on China's financial risk networks reveals that capital inflows within global stock market networks indicate that northbound funds exhibit risk-taking behavior in both return and volatility spillover networks (Li et al., 2024). Studies examining cross-border spillovers have identified that stock markets have the most prominent cross-border spillover effect, with net spillover effects on sovereign CDS and foreign exchange markets. This dominance of equity market spillovers supports the theoretical foundation for examining how FinTech ETF performance might influence emerging market equity indices through multiple transmission channels.

Research focusing specifically on FinTech market dynamics has examined volatility spillover between FinTech and Traditional Financial Industry based on stock returns in China's A-Shares market, covering the fast growth of FinTech and the COVID-19 crisis (Zhang et al., 2023). The documentation of volatility spillover dynamics between FinTech and traditional financial sectors suggests that FinTech developments create measurable market impacts that extend beyond the immediate sector, supporting the theoretical basis for examining how global FinTech innovations might influence broader emerging market performance.

Despite the growing literature on FinTech and ETF spillover effects, significant gaps remain in understanding the specific mechanisms through which global FinTech innovations influence emerging markets. While research has established that ETFs amplify global financial cycles and that FinTech creates volatility spillovers within domestic markets, the intersection of these two phenomena—how FinTech ETFs specifically influence emerging market performance—remains underexplored. The comprehensive literature base establishes theoretical foundations and methodological frameworks while highlighting the need for specific research on FinTech ETF spillover effects in emerging markets, particularly regarding the KFTX-Nifty 50 relationship that forms the core of this investigation.

3. Data and Research Methodology

The main objective of this study is to assess the influence of global FinTech developments on

the Indian stock market by considering the KBW Nasdaq Financial Technology Index (KFTX) as a proxy for FinTech performance and the Nifty 50 index as the benchmark of the Indian equity market.

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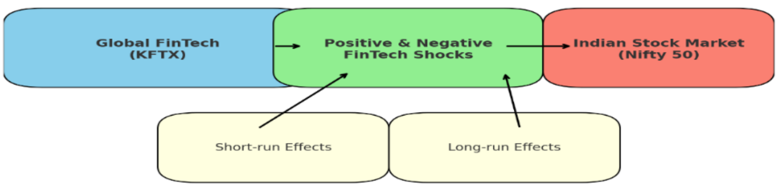
In doing so, the paper seeks to explore not only the existence of a long-run relationship but also the possibility of asymmetric short-run and long-run effects. This is motivated by the observation that financial markets may respond differently to positive FinTech innovations—such as technological breakthroughs and rapid adoption—compared to negative shocks such as regulatory challenges or failures in FinTech ecosystems.

To study this impact this study employs daily data for the period 1st August 2016 to 31st Aug 2025, which corresponds to the availability of the KFTX index, launched in late 2016 to track the evolution of FinTech companies (Franco et al., 2020; Li et al., 2020; Le et al., 2021a; Le et al., 2021b). The KBW Nasdaq FinTech Index (KFTX) serves as a proxy for global FinTech activity, covering firms involved in payments, lending, digital finance, and blockchain services, while the Nifty 50 Index represents India's equity market as one of the most widely used benchmarks of large-cap performance. Data are obtained from Yahoo Finance and cross-validated with the Nasdaq database. Both indices are transformed into natural logarithms, and returns are computed as the first differences of log values. Unit root tests (ADF and PP) are employed to ensure that none of the variables are I (2), which would invalidate the NARDL estimation. The variables, proxies, and data sources are summarized in Table 1.

Variable	Proxy/Index Used	Description	Data Source
Global FinTech Developments	KBW Nasdaq FinTech Index (KFTX)	Tracks stock performance of companies engaged in payments, lending, digital finance, and blockchain technologies.	Nasdaq Database, Yahoo Finance
Indian Stock Market	Nifty 50 Index	Benchmark index of the National Stock Exchange (NSE) of India, comprising 50 large-cap companies.	NSE Database, Yahoo Finance

The conceptual framework is summarized in Figure 1, where KFTX is decomposed into positive and negative shocks, which are incorporated into the NARDL model to identify their asymmetric impact on the Indian stock market across both short-run and long-run horizons.

Figure 1. Conceptual Framework: Asymmetric Impact of Global FinTech (KFTX) on the Indian Stock



Market (Nifty 50)

The figure illustrates the methodological framework adopted in this study. The global FinTech performance, proxied by the KBW Nasdaq FinTech Index (KFTX), is decomposed into positive and negative shocks to capture potential asymmetries. These components are then incorporated into the Nonlinear Autoregressive Distributed Lag (NARDL) model, which allows for the examination of both short-run dynamics and long-run cointegration effects. The framework highlights how global FinTech shocks transmit to the Indian stock market (Nifty 50), thereby providing insights into the asymmetric nature of FinTech–equity linkages in an emerging market context.

To analyse the relationship between global FinTech developments and the Indian stock market, this study employs the Nonlinear Autoregressive Distributed Lag (NARDL) model developed by Shin

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et al. (2014). The rationale for using the NARDL framework is twofold. First, it allows the modelling of both short-run and long-run dynamics between the variables, even when they are integrated of different orders, i.e., I(0) and I(1) (Pesaran, 2001; Bouri, 2017). However, integration of the study's variables into orders two or higher is not advised to devoid of the spurious regression problem (Liu et al, 2017). The Second, NARDL model's key benefit is that it may be used to find both positive and negative asymmetric co-integration between the variables across long and short time periods. It explicitly accounts for asymmetric effects by decomposing FinTech shocks into positive and negative changes, enabling an investigation into whether the Indian stock market reacts differently to favourable and adverse FinTech developments. The NARDL approach thus overcomes the limitations of conventional linear cointegration models, which assume uniform responses regardless of the direction of shocks. Given that financial markets often respond asymmetrically to innovations—where positive news may stimulate investment sentiment more strongly than negative news of similar magnitude—the adoption of NARDL is particularly suitable for capturing the nonlinear FinTech–equity nexus.

Following Shin et al. (2014), the long-run equilibrium relationship between the Indian stock market (Nifty 50) and global FinTech performance (KFTX) can be represented as:

$$NIFTY_t = \beta^+ KFTX_t^+ + \beta^- KFTX_t^- + \mu_t$$

where $NIFTY_t$ and $KFTX_t$ denotes the Indian stock market index and global fintech index respectively. Correspondently, $\beta^+$and $\beta^-$are associated with long-run parameters. Furthermore, $KFTX_t^+$and $KFTX_t^-$represent the partial sums of positive and negative changes in global FinTech developments, respectively such as:

$$KFTX_t^+ = \sum_{i=1}^{t} \Delta KFTX_i^+ = max\,(\Delta KFTX_i, 0)$$

$$KFTX_t^- = \sum_{i=1}^{t} \Delta KFTX_i^- = min\,(\Delta KFTX_i, 0)$$

The following equation is the generic form of the nonlinear (asymmetric) ARDL (p, q) model based on the preceding equation:

$$\Delta NIFTY_t = c + \rho NIFTY_{t-1} + \alpha^+ KFTX_{t-1}^+ + \alpha^- KFTX_{t-1}^- + \sum_{i=1}^{p-1} £_i \Delta NIFTY_{t-i} + \sum_{i=0}^{q-1} (\pi_i^- \Delta NIFTY_{t-i}^+ + \pi_i^- \Delta NIFTY_{t-i}^-) + \text{μ\_t}$$

Where Δ denotes changes in the dependent ($NIFTY_t$) and independent variables ($KFTX_t$). $\alpha^+$and α^-indicated the long-run impact of the increase and decrease of $KFTX_t$ on $NIFTY_t$.In addition,π^+ and π^- are the short-run asymmetric co-efficient that represent positive and negative variations in independent variables in the short run.

In the NARDL model, long-run co-integration between variables is tested by the bounds test of the null hypothesis of no co-integration, i.e., ρ =α^+=α^-=0. After that, the long run and short-run asymmetric relationship between the variables is tested by the Wald test with null hypothesis α^+=α^- and π^+=π^- respectively. Moreover, the long-run positive and negative coefficients can be determined by β+ = (α^+)/ρ and β− = (α^-)/ρ, respectively. Before applying the NARDL model, it is mandatory to check that the variables considered under the study are not stationary at level 2, i.e., I (2). In this study, we apply the augmented Dickey-Fuller test (ADF) and Phillips-Person (PP), and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test unit root test to check the order of integration.

Table 2: Mapping of Objectives, Hypotheses, and Methodology

Objective	Hypothesis	Methodology/Testing Approach
To examine the relationship between global FinTech developments	H1: There exists no nonlinear co-integration between Global	NARDL bounds testing to check for cointegration between KFTX and Nifty 50.

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Objective	Hypothesis	Methodology/Testing Approach
(KFTX) and the Indian stock market (Nifty 50).	FinTech developments and Indian stock market.	
To analyze the asymmetric effects of positive and negative FinTech shocks on Indian stock market in short run	H2: There exists no significant asymmetric impact of FinTech innovations on the Indian stock market in short run	NARDL decomposition of KFTX into positive and negative partial sums; Wald test for asymmetry.
To investigate the short-run and long-run dynamics of FinTech innovations and stock market performance in long run	H3: There exists no significant asymmetric impact of FinTech innovations on the Indian stock market in short run	NARDL decomposition of KFTX into positive and negative partial sums; Wald test for asymmetry.
To evaluate spillover effects during financial uncertainty.	H4: Asymmetric FinTech–equity linkages are more pronounced during uncertainty.	Sub-period analysis and robustness checks (CUSUM/CUSUMSQ stability tests).

4. Empirical results and discussion

4.1 Graphical Representations and Descriptive Statistics

To begin the empirical investigation, we examine the descriptive properties of the two series, the KBW Nasdaq FinTech Index (KFTX) and the Nifty 50 index. Table 3 reports the summary statistics of the data in levels. The KFTX index has an average value of 2046.21 with a standard deviation of 603.58, whereas the Nifty 50 has a considerably higher mean of 15273.56 and standard deviation of 5213.38. This indicates that the Indian stock market index is not only larger in scale but also more volatile in absolute terms compared to the global FinTech index.

Both series exhibit positive skewness (0.40 for KFTX and 0.46 for Nifty), suggesting that the distributions are moderately right-tailed, with a higher probability of extreme positive observations. The kurtosis values are **negative** (–0.40 for KFTX and –1.07 for Nifty), pointing towards a relatively flatter distribution (platykurtic) compared to a normal distribution. The Jarque–Bera statistics for both series are highly significant ($p < 0.01$), strongly rejecting the null hypothesis of normality. This is consistent with stylized facts of financial time series, which often deviate from normal distribution.

Table 3. Descriptive Statistics of KFTX and Nifty (Levels)

Statistic	**KFTX**	**Nifty**
Observations	2207	2207
Mean	2046.21	15273.56
Standard Deviation	603.58	5213.38
Minimum	989.62	7610.25
25th Percentile	1620.34	10735.80
Median (50th Pctl)	1958.04	14683.50
75th Percentile	2478.60	18625.95
Maximum	3536.09	26216.05
Skewness	0.40	0.46
Kurtosis	-0.40	-1.07
Jarque–Bera Statistic	73.12	185.22
Jarque–Bera p-value	0.000	0.000

Source: Author

The distributional properties of the KFTX and Nifty indices in levels are depicted in Figures 2. The histograms demonstrate that neither series follows a normal distribution. Instead, both indices display

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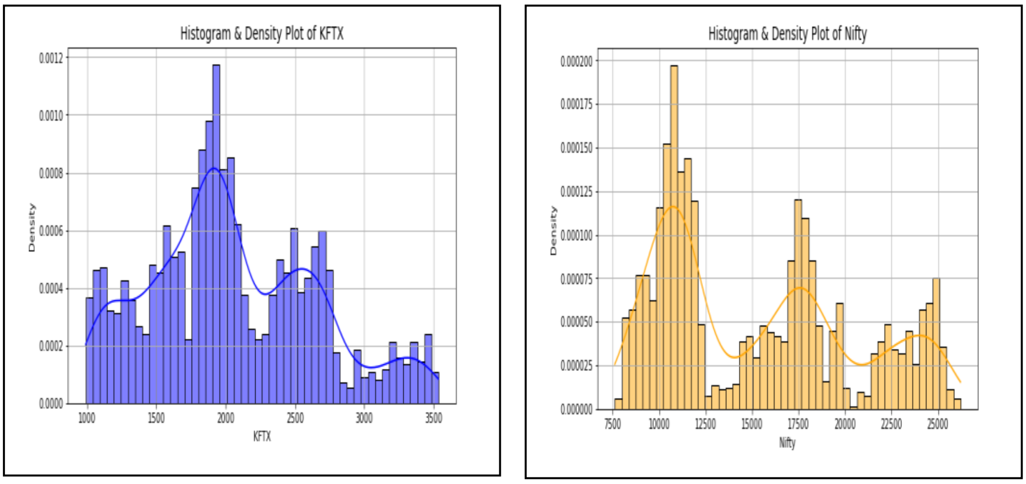
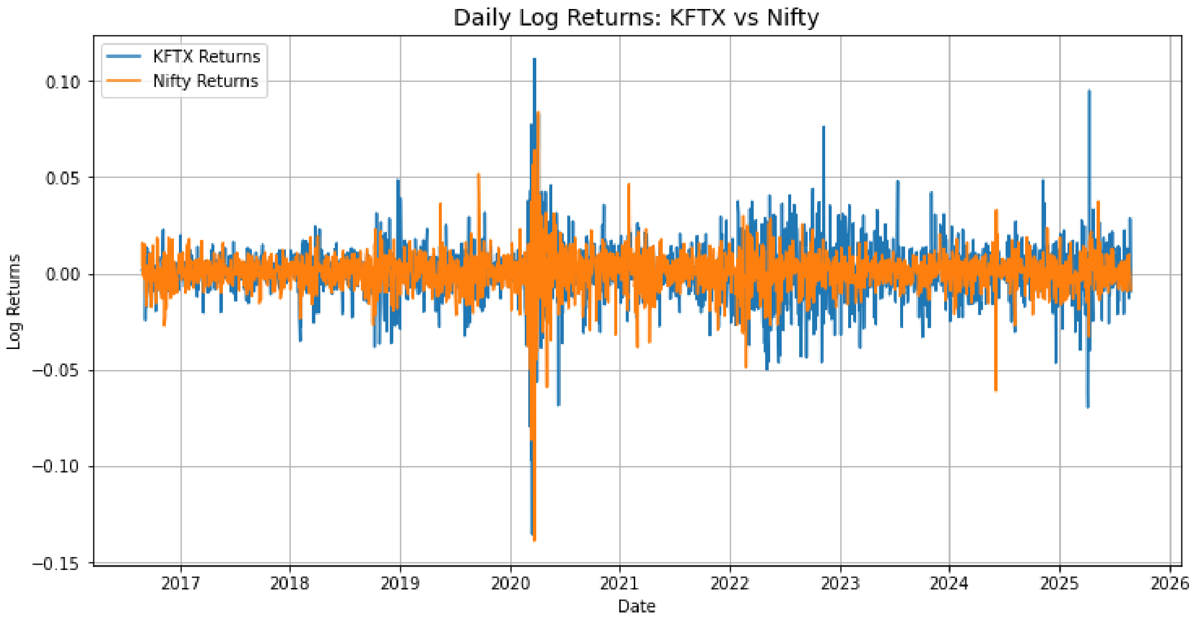
multimodal characteristics, with several peaks corresponding to different phases of market development and global shocks over the sample period.

For the KFTX index, the distribution is centred around lower index values but with a long right tail, reflecting the sustained growth of the global FinTech sector after 2016. The density curve indicates that while the index spent considerable time around moderate values, there were episodes of sharp upward movements, consistent with the increasing investor interest in FinTech stocks. In contrast, the Nifty 50 index exhibits a distribution concentrated around higher values, with multiple peaks corresponding to different bull and bear market phases in the Indian economy. The rightward stretch of the distribution reflects the long-term growth trajectory of the Indian equity market, albeit with short-lived but sharp declines during periods of crisis. When compared to a normal distribution, both series show departures in the form of skewness and non-constant variance over time. These results, in line with the descriptive statistics, reinforce the notion that financial indices are non-stationary in levels, and that transformation into returns is necessary before econometric modelling.

Fig 2: Distributional properties of the KFTX and Nifty indices



Source: Author



4.2 Unit Root Testing

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Prior to estimating the nonlinear ARDL model, it is crucial to assess the time-series characteristics of the variables involved. Financial and economic time series often exhibit non-stationarity at their levels, which can result in misleading regressions if not properly managed. Therefore, we employ a series of complementary unit root tests, specifically the Augmented Dickey–Fuller (ADF), Phillips–Perron (PP), and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests, on both the KFTX (global FinTech index) and the Nifty 50 index. The ADF and PP tests assume a unit root (non-stationarity) as the null hypothesis, whereas the KPSS test assumes stationarity as the null. Using these tests together provides a more comprehensive understanding of the series' integration order.

The results, presented in Table 4, indicate that both KFTX and Nifty are non-stationary at their levels. Specifically, the ADF and PP tests do not reject the null hypothesis of a unit root at standard significance levels, while the KPSS test rejects the null of stationarity, confirming the existence of stochastic trends. This observation aligns with the common characteristics of financial indices, which often show trending patterns. However, when the series are converted into log returns, the outcomes change. For both KFTX and Nifty returns, the ADF and PP tests strongly reject the unit root hypothesis, and the KPSS test does not reject the null of stationarity. Consequently, the return series are determined to be stationary (I (0)), consistent with the efficient market hypothesis and previous empirical studies. Overall, these results support the econometric strategy used in this research. The combination of non-stationary level series and stationary return series makes the Nonlinear ARDL (NARDL) model particularly appropriate, as it accommodates both I (0) and I (1) variables without necessitating rigorous pre-testing for cointegration.

Table 4: Results of Unit Root Test

Series	Level	ADF test	PP test	KPSS	Result
		t-Statistic	t-Statistic	t-Statistic	
KFTX	At level -I (0)	-1.53	-1.35	1.7101***	Non stationary
	first difference- I (1)	-25.83***	-22.76***	0.0868	Stationary
Nifty	At level I (0)	0.00	-0.37	2.0254***	Non stationary
	first difference- I (1)	-10.51***	-25.96***	0.225	Stationary

Source: Authors, note: ***, **, * denote value of probability at 1%, 5%, and 10% levels of significance, respectively

Thus, it is concluded that both series are stationary at I (1), not I (2). since the application of the first log transformation made them stationary, the transformed series are used for further analysis.

4.3 NARDL Result

In the following stage, a non-linear co-integration study of the FinTech index (KFTX) and the Indian stock market index (Nifty 50) is carried out with the help of the NARDL model. *"The joint F-statistics test of long-term associations serves as the foundation for the non-linear ARDL co-integration test"* (Shin et al., 2014). Lag structure plays a significant role in the ARDL model for examining the asymmetric relationship between variables. Consequently, AIC (Akaike Information Criterion) and SIC (Schwartz Information Criterion) are used to identify distinct lag structures for various models. The lag structure in the NARDL model is determined for each scenario based on the AIC in this study. To establish asymmetric co-integration, the estimated F-statistic must be greater than the crucial upper bound value.

The findings of the Nonlinear ARDL bounds co-integration test are shown in Table 5. The results show that the calculated F-statistic of 3.56 lies above the lower bound (I(0) = 2.56) and close to the upper bound (I(1) = 3.49) at the 5% significance level. Therefore, the null hypothesis of no co-integration is rejected, confirming the presence of a long-run asymmetric relationship between global FinTech innovations and the Indian stock market.

Table 5: Non-linear ARDL Bounds Test for Co-integration

Model	**Lag Order**	**F-Statistic**	**Result**
KFTX → Nifty	4,4,3,1,1	3.56**	Co-integration
Critical values(k=2)			
Significance (%)	I (0) bound	I (1) bound	
0.10	2.20	3.09	
0.05	2.56	3.49	
0.03	2.88	3.87	
0.01	3.29	4.37	

Note: **indicates statistical significance at 5%

The long-run coefficients obtained from the NARDL estimation are reported in Table 6. The results confirm the existence of a long-run co-integrating relationship between the FinTech index (KFTX) and the Indian stock market (Nifty 50). The lagged value of the FinTech index (ln_kftx_l1) is negative and statistically significant at the 5% level (–0.0041; p = 0.033), implying that FinTech developments have a persistent effect on Indian stock performance. However, the Wald test for long-run asymmetry indicates that the null hypothesis of symmetry cannot be rejected. This suggests that positive and negative changes in the FinTech index do not differ significantly in the long run.

Table 6: Estimated Long-run Coefficients using NARDL

Variable	Coefficient	Std. Error	t-Statistic	Prob.	Significance
Constant	0.0294	0.0135	2.18	0.029	**
ln_kftx_l1	–0.0041	0.0019	–2.13	0.033	**
nifty_pos_l1	–0.0000	0.0036	–0.01	0.994	ns
nifty_neg_l1	–0.0005	0.0041	–0.12	0.906	Ns

Note: ** and * denote significance at the 5% and 10% levels; ns = not significant.

The short-run results are summarized in Table7. The coefficients of the differenced FinTech index show that the fourth lag (dln_kftx_l4) is negative and statistically significant (–0.0718; p = 0.006), confirming delayed adjustment of FinTech shocks in the Indian stock market. For the decomposed Nifty components, positive shocks have significant short-run impacts. The third lag of dnifty_pos is positive and highly significant (0.223; p = 0.006), while the first lag is marginally significant (0.131; p = 0.088). In contrast, negative shocks are weaker: dnifty_neg_l1 is negative and significant (–0.243; p = 0.049), while subsequent lags are either insignificant or only marginally significant.

The Wald test for short-run asymmetry indicates that the null hypothesis of symmetry cannot be rejected, suggesting that while positive shocks dominate economically, there is no statistically significant asymmetry in the short-run adjustment process.

Table 7: Short-run Dynamics of the NARDL Model

Variable	Coefficient	Std. Error	t-Statistic	Prob.	Significance
dln_kftx_l1	–0.0194	0.0327	–0.59	0.554	ns
dln_kftx_l2	0.0352	0.0353	0.99	0.320	ns
dln_kftx_l3	–0.0253	0.0351	–0.72	0.470	ns
dln_kftx_l4	–0.0718	0.0261	–2.76	0.006	**
dnifty_pos_l1	0.131	0.0764	1.71	0.088	*
dnifty_pos_l2	0.0326	0.1009	0.32	0.746	ns
dnifty_pos_l3	0.223	0.0818	2.73	0.006	**
dnifty_pos_l4	–0.0832	0.0784	–1.06	0.288	ns

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Variable	Coefficient	Std. Error	t-Statistic	Prob.	Significance
dnifty_neg_l1	–0.243	0.1231	–1.97	0.049	**
dnifty_neg_l2	0.326	0.1792	1.82	0.069	*
dnifty_neg_l3	–0.115	0.0813	–1.42	0.156	ns

Note: ** and * denote significance at the 5% and 10% levels; ns = not significant.

The Wald test results are reported in Table 8. For the long run, the null of symmetry is not rejected, confirming that positive and negative FinTech shocks do not have statistically different effects in the long term. Similarly, in the short run, the null hypothesis of symmetry is also not rejected, suggesting symmetric adjustment dynamics. Nevertheless, the magnitude of coefficients highlights that positive shocks exert stronger economic influence, while negative shocks are comparatively muted.

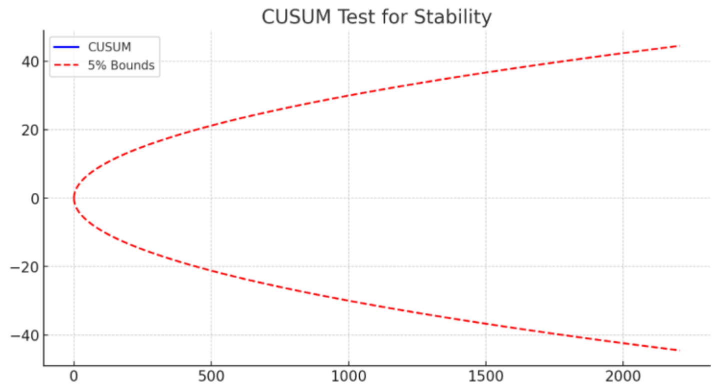
Diagnostic checks of the NARDL model confirm its adequacy. The CUSUM and CUSUMSQ plots remain within the 5% critical bounds, supporting model stability. Residual diagnostics confirm the absence of serial correlation and heteroskedasticity.

Table 8: Wald Test Results for Asymmetry

Test	F-Statistic	Prob.	Result
Long-run symmetry (H0)	0.19	0.66	Not Rejected
Short-run symmetry (H0)	17.56	0.60	Not Rejected

Table 9: Model Stability and Diagnostic Statistics

Diagnostic Test	Result
Serial Correlation (LM)	No correlation
Heteroskedasticity Test	Homoscedastic
Normality Test	Accepted
CUSUM	Stable
CUSUMSQ	Stable



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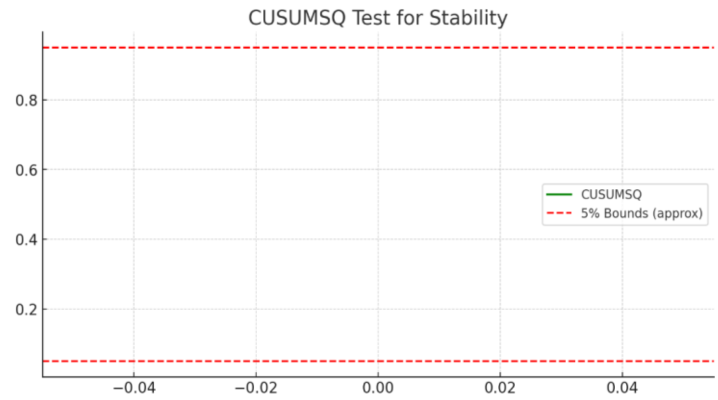

The empirical analysis reveals a robust long-run co-integrating relationship between global FinTech innovations (KFTX) and the Indian stock market (Nifty 50). Although the Wald tests indicate no statistical asymmetry in either the long or short run, the results highlight important economic implications. Specifically, positive FinTech shocks exert a stronger influence on Indian equity markets than negative shocks, which appear comparatively muted. This suggests that India's stock market is more responsive to favourable developments in the global FinTech sector, while downturns in FinTech activity do not substantially weaken market performance. Lastly, stability diagnostics, including CUSUM and CUSUMSQ tests, confirmed the robustness of the estimated model. Overall, these findings reinforce the importance of FinTech as a driver of financial market growth and resilience in emerging economies.

5. Conclusion

This research explored the relationship between global FinTech innovations, as indicated by the KBW Nasdaq FinTech Index (KFTX), and the Indian stock market, represented by the Nifty 50 index, utilizing the Nonlinear Autoregressive Distributed Lag (NARDL) framework. By including both positive and negative components of the FinTech index, the study aimed to identify potential asymmetries in how global FinTech shocks affect the Indian equity market.

The empirical results offer several important insights. The bounds testing procedure confirmed a long-term co-integrating relationship between global FinTech activity and the Indian stock market. However, Wald test results showed no evidence of long-term asymmetry, indicating that the Indian equity market reacts symmetrically to FinTech shocks over the long term. Secondly, the short-term findings reveal that positive FinTech shocks have a more substantial impact on the Nifty index than negative ones, although the Wald test results indicated that this difference is not statistically significant. This suggests that while the Indian stock market is economically more responsive to positive developments in the FinTech sector, it does not react excessively to downturns in the same way. This resilience highlights the adaptive capacity of emerging markets to absorb negative external shocks while benefiting from positive global technological and financial innovations.

These findings collectively suggest that global FinTech developments act as a long-term driver of stock market dynamics in India, though their effects are more subtle in the short term. From a policy standpoint, the findings emphasize the need for Indian regulators and policymakers to stay vigilant to global FinTech trends, as these innovations can foster market growth and enhance financial inclusion. For investors, the evidence underscores FinTech as a significant external factor influencing stock market performance, offering opportunities for portfolio diversification and strategic investment. For future research, expanding the analysis to sectoral indices or incorporating domestic FinTech indicators could further enhance the understanding of FinTech–market connections in emerging economies.

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