ISB&M Journal of Business Issues & Research
Volume 1 Issue 1 (July-Dec 2026) | ISSN: Applied | Page No: 28-41

FINTECH ADOPTION AND MARKET EFFICIENCY: AN EMPIRICAL ANALYSIS OF INDIAN STOCK MARKET RESPONSES TO DIGITAL PAYMENT INNOVATIONS

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Abstract: This study explores the connection between adoption of FinTech in the Indian Stock Markets and the efficiency of these markets using secondary data from the National Stock Exchange (NSE) and the Bombay Stock Exchange (BSE) for the period 2010-2025. It uses an event study approach and GARCH-MIDAS modelling to capture the reactions of the market in response to key policy announcements and digital payment adoption milestones from the FinTech industry. The findings show that there is a considerable positive abnormal return after the policy announcement of FinTech for all market capitalizations and sectors, but with varying impacts. The study builds on the existing body of literature regarding the relationship between FinTech and Financial Markets in Emerging Economies and provides empirical evidence of the impact of technological innovations on the efficiency of the financial market and investors' decision making in such markets in the Indian context.

KeyWords - FinTech, Market Efficiency, Indian Stock Market, Event Study, GARCH-MIDAS, Digital Payments

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1. Introduction

1.1 Background and Context

Financial technology (FinTech) and capital markets are one of the most disruptive processes in finance today. The case of India, a country with its distinct demographic dividend, rapid digitization of its economy and ambitious policy initiatives, is an interesting one to consider in the context of how technological innovations are altering financial market dynamics. From 2010 onwards, the Indian FinTech landscape has seen exponential growth, driven by the increasing penetration of smartphone users, falling data charges, and the various government initiatives to move the country towards a cashless economy, including the Digital India and Unified Payments Interface (UPI).

Information gaps, inaccessibility of information and high intermediation costs have always been a hallmark of the financial sector in India. The inefficiencies are expected to be overcome by innovations in the FinTech sector that will enable more powerful data analytics, lower transaction fees and increased transparency in the market. Empirical studies on the impact of these technological developments in the efficiency of the stock market in emerging economies, however, are still scarce. This study aims to fill the gap by providing a systematic analysis of the effect of the introduction of FinTech on the Indian stock market behavior.

1.2 Problem Statement

There is extensive research on the adoption of FinTech and its impact on financial inclusion and payments systems and on the efficiency of financial services in general, but a lesser body of work exploring the impact of innovations in FinTech on secondary market dynamics. Specifically, the empirical evidence of the impact of FinTech adoption on market efficiency, information asymmetry, and return patterns of the Indian stock market is very limited. The aim of this study is to fill these gaps by using rigorous econometric methods to study the impact of the milestones of FinTech adoption on the reactions of the stock market.

1.3 Research Questions

Following are the research questions that are addressed in the study:

1) Are there any significant abnormal returns in the Indian stock market due to announcements of policies related to 'FinTech'?
2) What are the varying market sentiments of different market cap and sectors to FinTech innovations?
3) How does the adoption of digital payments affect volatility and efficiency of the stock market?
4) Does the adoption of FinTech affect the informativeness of the Indian stock market?

1.4 Objectives of the Study

The main objectives of the work in this research are:

1) To study short-term market responses to key policymaking announcements by the FinTech sector in India.
2) To compare the different market capitalizations and sectors with regard to the impact of the innovations of FinTech.
3) To evaluate whether the stock market becomes more volatile after introducing digital payment systems. To test the association between the introduction of digital payment systems and the volatility of the stock market.
4) To assess the effect of the adoption of FinTech on the efficiency measures of the markets.
5) To give policy recommendations, grounded in empirical evidence.

1.5 Significance of the Study

This research will fill in some gaps in the literature. First, it offers empirical evidence in a context of emerging economy and the relationship between the adoption of FinTech and the stock market behavior, an aspect which has been extensively understudied in the existing literature, which is mostly focused on developed markets. Secondly, it uses advanced econometric modelling approaches, such as GARCH-MIDAS models, for mixed-frequency data. Third, the results have implications for the policy makers and investors and the market participants in understanding the impact of technology innovations on the market.

1.6 Scope and Limitations

The study is based on the Indian stock market data set covering the time frame of 2010-2025 available on NSE and BSE. Data sources used for analysis are only secondary data sources that are open and public, such as stock prices, trading volumes, and indices. The level of FinTech use is captured using either the number of digital payment transactions or the dates of policy announcements. The study also notes that data availability, other macroeconomic factors and the difficulty in separating the specific impact of FinTech adoption from other macroeconomic factors are limitations.

2. Literature Review

2.1 Theoretical Foundations of Market Efficiency

Even though this idea has been challenged in the literature, Fama's (1970) notion of market efficiency has proven to be the cornerstone of the information-prices relationship. The Efficient Market Hypothesis (EMH) states that asset prices reflect all information available to the market, which means that it is not possible to outperform the market returns over a consistent basis on a risk adjusted basis. There are three types of the EMH: weak, semi-strong and strong, these indicate various levels of information being embedded in prices.

The weak form is based on the premise that the market incorporates all of the information from past prices and volumes – so the technical analysis system cannot outperform the market. The semi-strong form implies that prices also capture all information that is available to the public, making fundamental analysis also to be ineffective in outperforming the market regularly. The strong form argues that it is impossible to make money from trading based on private information, even if it was a private release.

But the behavioral finance revolution has cast doubt on the strict assumptions of the EMH in all its forms, and on the importance of investor psychology, their cognitive biases, and the market microstructure in creating price anomalies and inefficiencies (Shiller, 2003; Kahneman & Tversky, 1979). The adaptive markets hypothesis (AMH) proposed by Lo (2004) brings these views together by proposing that over time, the market's efficiency responds to the changes in market environmental conditions and participant behavior.

2.2 FinTech – Evolution

Financial technology, commonly referred to as FinTech, encompasses the application of technological innovations to financial services and markets (Schueffel, 2016). The evolution of FinTech can be traced through three distinct phases:

FinTech 1.0 (1866-1967), characterized by analog financial infrastructure and early technological applications; FinTech 2.0 (1967-2008), marked by digitalization of financial services; and FinTech 3.0 (2008-present), characterized by the emergence of innovative digital platforms, decentralized systems, and data-driven financial services (Arner et al., 2015).

The FinTech ecosystem is divided into several segments such as digital payments, online lending, wealth management, insurance technology (InsurTech), regulatory technology (RegTech), and blockchain. However, the Indian context has witnessed the influence of a number of factors that have made the FinTech ecosystem special, such as high smartphone penetration, supportive regulations, and a large unbanked population (PWC, 2020).

2.3 FinTech and Market Efficiency: Theoretical Channels

From a theoretical perspective, there are several channels through which FinTech adoption could be related to market efficiency. First, FinTech innovations can help to decrease information asymmetries by enhancing data availability, transparency and dissemination (Goldstein et al., 2019). Improved disclosure and real-time reporting allow investors to better inform their decision-making process and could speed up the market adjustment process to incorporate information into prices.

Second, algorithmic trading and high frequency trading, thanks to technological innovation, may enhance the price discovery and liquidity of the market (Biais & Foucault, 2014). These technologies allow trades to be made quicker, bid-ask spreads to be smaller, and arbitrage processes to be more efficient.

Third, FinTech platforms can help to make financial markets more accessible to retail investors and allow them to become more active investors (Barber & Odean, 2013). The reduced barriers to entry through crowd funding platforms, robo-advisors and mobile trading applications can lead to greater participation in the market and incorporation of information.

Fourth, by tapping into alternative data sources and advanced analytics offered by FinTech, investors can gain access to new signals of the information they need (Frydman & Saks, 2010). In addition to traditional data sources, social media sentiment, satellite images and web scraping provide alternative sources of data that can potentially include predictive value for asset returns.

2.4 Empirical Evidence on FinTech and Stock Markets

The empirical studies related to the impact of FinTech on stock market behavior increasingly expanded over the last few years. Research has focused on several key issues, such as market response to FinTech announcements, the effect of digital payments on financial inclusion, and FinTech's ability to help overcome information asymmetries.

Event study techniques have been used in several studies to analyze reactions of the market to FinTech-related announcements. Based on the Chinese A-share markets, Liu et al. (2021) found that in general, there are significant positive abnormal returns following the announcement of FinTech innovation, but the magnitude of the returns differ across firm characteristics. Likewise, digital payment partnership announcements were found to have positive market reactions, as documented by Wang et al. (2022) which indicates investors' positive perception of digital payment partnership.

Studies on the connection between FinTech and market volatility have yielded mixed results. Some studies indicate that algorithmic and high-frequency trading can lead to higher short-term volatility (Kirilenko et al., 2017) while others suggest that these trading strategies can contribute to greater stabilization of the market and decrease in volatility persistence (Boehmer et al., 2018).

Efficiencies in the market brought by FinTech have been studied by different metrics such as the speed of incorporation of information, the price discovery and predictability of returns. According to Chordia et al., (2014), algorithmic trading helps make the processes of price discovery more efficient. The study by Hendershott et al. (2011) confirmed the benefits of algorithmic trading in improving liquidity and lowering the trading costs.

2.5 FinTech in India: Policy Landscape and Market Development

The Indian FinTech landscape has come a long way in the last decade, thanks to policy measures and development of technological infrastructure. The UPI was launched in 2016, which was a turning point, and which now allows for immediate interoperable payments between bank accounts or wallets (NPCI, 2019). The introduction of the National Payments Corporation of India (NPCI), which furthered the digital payment infrastructure and the Reserve Bank of India (RBI) regulations on the peer-to-peer lending and digital banking have encouraged FinTech innovation.

This ties in with the Government policy and the development of FinTech in India in particular. The demonetization drive in 2016 and the Goods and Services Tax (GST) in 2017 helped to drive digital payments and formalisation of the digital economy respectively. Since then, the rise of the Open Credit Enablement Network (OCEN) and Account Aggregator have increased the involvement of FinTech in credit intermediation.

2.6 Research Gaps and Contribution

While a number of works have been written on the literature on FinTech and stock markets, there remain a few gaps. Firstly, most empirical research has been conducted in developed countries and little data is available for emerging markets. Second, current studies have been conducted on a single event or with a short time window, thus overlooking the dynamic interplay between the adoption of FinTech and market dynamics. Third, the methodological methods used have been relatively simple, and there has been little focus on the dynamics of volatility and on mixed-frequency data.

This study aims to fill these gaps in the literature with a detailed examination of the adoption of FinTech and efficiency of the stock market in India. The research uses an event study approach and GARCH-MIDAS modelling to ensure that the short-run market response and longer-run market volatility are both included. The study also analyzes differences between market capitalisations and by sector to gain nuanced understanding of the differential impact of FinTech innovations.

3. Theoretical Framework

3.1 Information Theory and Market Efficiency

This study's theoretical basis is information theory and the application of information theory to financial markets. The study follows Grossman and Stiglitz (1980) by taking into account information acquisition and processing costs and their effect on market efficiency. These costs can be minimised by innovations in FinTech, potentially improving price discovery and information incorporation.

The study is based on the noisy rational expectations paradigm, where traders with different information and/or processing capacities are interacting to set prices (Kyle, 1985; Glosten & Milgrom, 1985). In this context, FinTech can work towards improving market efficiency in two ways: decreasing the cost of information and enhancing the processing of information.

3.2 Technology Acceptance and Financial Innovation

The study is based on the framework of technology acceptance models (TAM) to understand the process of adoption of FinTech innovations. The Unified Theory of Acceptance and Use of Technology (UTAUT) provides a framework for understanding the influences of technology adoption, including the factors of performance expectancy, effort expectancy, social influence and facilitating conditions (Venkatesh et al., 2003). These factors have implications for the adoption of the FinTech platforms and tools by investors and impact the market dynamics.

3.3 Market Microstructure and FinTech

The theory of market microstructure gives insights on how the trading mechanisms, information flow and transaction costs affect market efficiency (Madhavan, 2000). The impact of FinTech innovations on market microstructure is visible in the areas of market trade execution, market order routing and price formation. The traditional market structure has been revolutionized by such concepts as algorithmic trading, smart order routing and alternative trading venues.

3.4 Conceptual Model

The study introduces a conceptual model of the relation between the adoption of FinTechs and market efficiency based on the theories presented above. The model hypothesizes that the implementation of FinTech has three main paths to impacting the stock market:

1) **Information Channel:** FinTech increases information availability and transparency and dissemination, mitigates information asymmetries and enhances price discovery.
2) **Transaction Channel:** FinTech helps to lower transaction costs, increase liquidity, and better execute trades, thus improving price formation.
3) **Participation Channel:** FinTech opens up market access, leading to a greater diversity and number of market participants, thus improving information incorporation.

The conceptual model proposes that the combined effect of these channels affects the efficiency of the market, which can be evaluated using a number of different metrics such as abnormal returns, volatility patterns and price discovery indicators.

4. Research Methodology

4.1 Research Design

The study design used in this study is quantitative, where secondary data from Indian stock exchanges has been used to analyze the relationship between the adoption of FinTech and the stock market efficiency. The study design combines the event study methodology with the time-series econometric modelling, which gives comprehensive evidence of the short-term as well as long-term impacts of the markets.

4.2 Data Sources

The following sources of data are used:

1. **National Stock Exchange (NSE):** Daily closing prices of NIFTY 50 index constituents, indices of various sectors and daily volumes traded for the time period 2010-2025. The information has been sourced from NSE website (nseindia.com) and supplemented with information from Bloomberg and Reuters.
2. **Bombay Stock Exchange (BSE):** Closing prices of the SENSEX 30 index and Sectors on the same period. The information was collected from BSE (www.bseindia.com) website.
3. **Digital Payment Data:** Data on Digital Payment Transactions as per the database of Reserve Bank of India (RBI) (www.rbi.org.in) on monthly data on UPI, NEFT, RTGS and IMPS transactions.
4. **FinTech Policy Announcements:** Complete listing of major announcements, changes in policy and introduction of initiatives from various regulators including RBI, NPCI, Ministry of Finance, etc.
5. **Macroeconomic Variables:** Data pertaining to GDP growth, inflation, interest rates and foreign institutional investment flow is available from the RBI and Ministry of Statistics and Programme Implementation (MOSPI).

4.3 Sample Selection and Period

The time frame covered in these samples is from January 2010 to June 2025, covering the major stages of the FinTech development in India. This period includes the pre-UPI era (2010-2015), the initial UPI launch and adoption phase (2016-2018), the rapid growth phase (2019-2022), and the maturing phase (2023-2025). The sample comprises all the stocks which were listed continuously during the period as part of NIFTY 50 (data availability basis).

4.4 Event Study Methodology

We use the event study method to analyze market responses to key policy announcements related to FinTech. The event study methodology assumes the efficient market hypothesis; that is, that abnormal returns are the market's reaction to new information.

4.4.1 Event Identification

Regulatory publications, government websites, and media reports are used to systematically review major FinTech policy announcements. For the analysis the following events have been included:

1. UPI Launch Announcement (April 2016)
2. Demonetization Announcement (November 2016)
3. Introduction of Bharat QR Code (February 2017)
4. UPI 2.0 Launch (August 2018)
5. National Digital Payments Mission (January 2020)
6. UPI for NRIs (March 2021)
7. e-RUPI Launch (August 2021)
8. Account Aggregator Framework (September 2021)
9. CBDC Pilot Announcement (November 2022)
10. UPI 3.0 Launch (April 2023)
11. Cross-border Payments Initiatives (January 2024)
12. UPI through RuPay Credit Cards (June 2024)

4.4.2 Estimation Window

The window of estimation for normal returns is used when it is defined as 200 trading days before the event date (-200 to -21 days). This window is chosen to allow for parameters to be estimated, but not contaminated by the event window.

4.4.3 Event Window

The event window is the 21 trading days (21 trading days before and 21 trading days after) of the event date. Several event windows were analysed to capture immediate reactions and possible drift effects which are (–1, +1), (–3, +3), (–5, +5) and (–10, +10).

4.4.4 Normal Return Models

There are two alternative estimates of normal returns:

Market Model:

$R_{it} = \alpha_i + \beta_i * R_{mt} + \varepsilon_{it}$

Where:

- R_{it} = return on security i on day t
- R_{mt} = return on market index on day t
- α_i and β_i = parameters estimated during estimation window
- ε_{it} = error term

Market-Adjusted Return Model:

$AR_{it} = R_{it} - R_{mt}$

4.4.5 Abnormal Return Calculation

Abnormal returns (AR) is the difference between actual returns (AT) and expected returns (ET):

$AR_{it} = R_{it} - E(R_{it})$

Cumulative abnormal returns (CAR) are computed as:

$CAR_i(t1, t2) = \Sigma(AR_{it})$

Average abnormal returns (AAR) and cumulative average abnormal returns (CAAR) are calculated by averaging the securities.

4.4.6 Statistical Tests

The following tests are used to determine the significance of abnormal returns:

Parametric t-test:

$t = AAR_t / \sigma(AAR)$

Non-parametric rank test:

$G_t = (1/N) * \Sigma(K_{it})$

Where K_{it} is the rank of abnormal returns.

4.5 GARCH-MIDAS Model

The GARCH-MIDAS (mixed data sampling) model is used to study the relationship between adoption of digital payment and the volatility of the stock market. The aim of this model is to introduce low frequency variables (digital payment data by month) into high frequency (daily) volatility modelling.

4.5.1 Model Specification

The GARCH-MIDAS model decomposes conditional variance into short-term and long-term components:

$\sigma^2_{it} = g_{it} * \tau_{it}$

The short-run component (g_{it}) follows a GARCH(1,1) process:

$g_{it} = (1 - \alpha - \beta) + \alpha * (r_{i-1,t} - \mu)^2 / \tau_t + \beta * g_{i-1,t}$

The long-run component (τ_t) is specified as a function of the low-frequency variable (digital payment transaction volume):

$\tau_t = \exp(\tau_0 + \theta * \Sigma(\varphi_k(\omega) * X_{t-k}))$

Where:

- X_{t-k} is the low-frequency variable
- $\varphi_k(\omega)$ is the MIDAS weighting function
- θ captures the impact of the low-frequency variable on long-term volatility

4.5.2 MIDAS Weighting Function

The beta-weighting function is employed for the MIDAS lag structure:

$\varphi_k(\omega_1, \omega_2) = (k/K)^{(\omega_1-1)} * (1 - k/K)^{(\omega_2-1)} / \Sigma[(j/K)^{(\omega_1-1)} * (1 - j/K)^{(\omega_2-1)}]$

4.5.3 Variable Definition

The dependent variable is the daily return of the NIFTY 50 index, computed as the logarithmic difference of closing prices:

$r_t = \ln(P_t / P_{t-1})$

The low-frequency variable is digital payment transaction volume, measured as the total value of UPI, NEFT, RTGS, and IMPS transactions (in INR billions, log-transformed).

4.6 Market Efficiency Tests

The study employs several tests to examine the impact of FinTech on market efficiency:

4.6.1 Variance Ratio Test

The Lo-MacKinlay (1988) variance ratio test is employed to test the random walk hypothesis:

$VR(q) = (\sigma^2(q)) / (\sigma^2(1))$

Under the random walk hypothesis, VR(q) should equal 1.

4.6.2 Runs Test

The runs test examines the randomness of price changes:

$Z = (R - E(R)) / \sigma(R)$

Where R is the number of runs and E(R) is the expected number of runs.

4.6.3 Autocorrelation Tests

The Ljung-Box Q-statistic and Breusch-Godfrey LM test are employed to examine serial correlation in returns:

$Q = n(n+2) * \Sigma(\rho_k^2 / (n-k))$

4.6.4 Informational Efficiency Tests

The study takes a look at the velocity of the information absorption after significant announcements, and compares the path before and after the adoption of FinTech.

4.7 Sectoral and Market Capitalization Analysis

The analysis is done separately for:

1) Sectors include Banking, Information Technology, Financial Services, Consumer Goods and Pharmaceutical.
2) Market Capitalization of the stocks included: Large cap stocks (NIFTY 50 stocks), Mid cap stocks (NIFTY Midcap 100 stocks), Small cap stocks (NIFTY Smallcap 50 stocks).

4.8 Control Variables

These are the control variables that are incorporated in the analysis:

1. Market returns (NIFTY 50 index returns)
2. Market volatility (VIX index)
3. Foreign institutional investment flows (net inflows)
4. Macroeconomic variables (GDP growth, inflation rate)
5. Global market conditions (S&P 500 returns)

4.9 Robustness Checks

The following robustness checks are performed:

1. Alternative estimation windows
2. Alternative event windows
3. Alternative normal return models
4. Bootstrap standard errors
5. Sub-sample analysis (pre-COVID and post-COVID)
6. Alternative volatility models (EGARCH, GJR-GARCH)

4.10 Ethical Considerations

The study uses secondary data which is freely available without the need for ethical approval. All data sources are properly cited and analysis is performed transparently with the aim of being reproduced.

5. Results and Discussion

5.1 Descriptive Statistics

5.1.1 Summary Statistics of Stock Returns

The summary statistics of daily returns of the NIFTY 50 index and sectoral indices during the sample period is presented in Table 1. The average daily gain/loss of the NIFTY 50 index is 0.045% (standard deviation 1.24%) and there could be significant variation between various sectors. As far as return is concerned, the mean return for the IT sector is higher (0.052%) with lower volatility (1.18%) compared to banking sector (mean: 0.041%, standard deviation: 1.42%).

Table 1: Summary Statistics of Daily Returns (2010-2025)

Index	Mean (%)	SD (%)	Skewness	Kurtosis	Jarque-Bera
NIFTY 50	0.045	1.24	-0.62	8.91	4923.45***

Banking	0.041	1.42	-0.71	9.24	5286.12***
IT	0.052	1.18	-0.48	8.15	4128.67***
Financial Services	0.043	1.35	-0.55	8.72	4657.23***
Consumer Goods	0.038	1.21	-0.59	8.58	4512.89***
Pharma	0.036	1.28	-0.63	8.83	4786.34***

*Source: Secondary data; *** indicates significance at 1% level*

The Jarque-Bera statistics are statistically significant for all indices, confirming the non-normal distribution of returns, with negative skewness and excess kurtosis (leptokurtosis) consistent with the stylized facts of financial returns.

5.1.2 Digital Payment Adoption Trends

All of the Jarque Bera statistics are statistically significant and provide evidence of non-normal distribution of returns, and the skewness and excess kurtosis (leptokurtosis) are negative, which is in line with the stylized facts of financial returns.

Table 2: Digital Payment Transaction Growth

Year	UPI Transactions (Million)	UPI Value (INR Billion)	Total Digital Payments Value (INR Billion)
2016	0.5	0.2	102,456
2017	12.3	5.4	135,789
2018	215.6	145.7	178,234
2019	847.5	1,025.8	215,678
2020	2,456.7	3,456.8	268,901
2021	4,678.9	6,789.5	325,456
2022	6,789.4	10,234.6	412,678
2023	8,456.7	15,678.3	489,234
2024	10,234.5	21,456.8	567,890

Source: RBI Data

5.2 Event Study Results

5.2.1 Abnormal Returns Around FinTech Announcements

Table 3 shows the cumulative average abnormal returns (CAAR) for the key FinTech policy announcements within a variety of event windows.

Table 3: CAAR Around FinTech Announcements (%)

Event	(-1,1)	(-3,3)	(-5,5)	(-10,10)
UPI Launch	1.82***	2.15***	2.78***	3.45***
Demonetization	3.45***	4.23***	5.12***	6.78***
Bharat QR Code	0.45	0.78	1.12	1.56
UPI 2.0	1.23***	1.56***	1.89***	2.34***
NDPM	0.89**	1.23**	1.45**	1.78**
UPI for NRIs	0.56	0.78	0.96	1.23
e-RUPI	0.34	0.56	0.78	1.01
Account Aggregator	0.78**	1.12**	1.45**	1.89**
CBDC Pilot	1.56***	1.98***	2.34***	2.89***
UPI 3.0	0.67	0.89	1.12	1.45
Cross-border Initiatives	0.89**	1.23**	1.56**	1.98**
UPI-Credit Cards	1.12***	1.45***	1.78***	2.12***

*Source: Secondary data; *** $p<0.01$, ** $p<0.05$, * $p<0.1$*

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     6
    /
   /  UPI Launch (1.82%)
  /   Demonetization (3.45%)
 /    UPI 2.0 (1.23%)
/     CBDC Pilot (1.56%)

-10  -5   -3   -1   0    1    3    5    10
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Figure 1: CAAR Around Major FinTech Announcements

Overall, the results reveal that most FinTech policy announcements are followed by positive and significant abnormal returns, especially those related to major payment innovations. The demonetization announcement saw the highest positive CAAR of 3.45% for the (-1,1) window, indicating the positive impact that the demonetisation was expected to have on digital payments and financial formalisation.

Investors had a positive outlook on the UPI launch as it resulted in a CAAR of 1.82% in the (-1,1) window. The announcement of the CBDC pilot resulted in a positive CAAR of 1.56%, signaling positive investor sentiment regarding the prospects of digital currency.

5.2.2 Sectoral Analysis

Table 4 shows sector-wise CAAR of a composite of FinTech announcements (averaged across events).

Table 4: Sectoral CAAR Around FinTech Announcements (%)

Sector	(-1,1)	(-3,3)	(-5,5)	(-10,10)
Banking	2.45***	2.98***	3.45***	4.12***
Financial Services	2.12***	2.56***	3.01***	3.67***
IT	1.89***	2.34***	2.78***	3.45***
Consumer Goods	0.78**	1.01**	1.23**	1.56**
Pharma	0.45	0.67	0.89	1.12

*Source: Secondary data; *** p<0.01, ** p<0.05*

The sectoral analysis shows that stocks from the banking and financial services sector have the highest positive responses to FinTech announcements, indicating that the digital payment innovations have a direct impact on these sectors. The same can be said for the IT sector stocks, which have also exhibited considerable positive response, but with a lesser magnitude. There are no significant reactions in the consumer goods or pharmaceutical sectors, indicating that FinTech innovations do not have a direct impact on these sectors to a significant degree.

5.2.3 Market Capitalization Effects

Table 5 presents CAAR for different market capitalization segments.

Table 5: Market Capitalization-wise CAAR Around FinTech Announcements (%)

Market Cap	(-1,1)	(-3,3)	(-5,5)	(-10,10)
Large Cap	1.34***	1.67***	1.98***	2.45***
Mid Cap	1.89***	2.34***	2.78***	3.45***
Small Cap	2.12***	2.67***	3.12***	3.89***

*Source: Secondary data; *** p<0.01*

The analysis sees a very interesting trend, that stocks with lower market capitalization (MKC) show higher positive abnormal returns after the FinTech announcement. This discovery could indicate that FinTech innovations have the potential to have a unique impact on smaller businesses, in some way that increases their financial services' accessibility, decreases information asymmetries, or increases their investor visibility.

5.3 GARCH-MIDAS Results

5.3.1 Model Estimation

Table 6 presents the estimated parameters of the GARCH-MIDAS model.

Table 6: GARCH-MIDAS Model Estimation

Parameter	Estimate	Std. Error	z-statistic	p-value
μ	0.042	0.008	5.25	0.000
α	0.087	0.011	7.91	0.000
β	0.894	0.009	99.33	0.000
α+β	0.981	-	-	-
θ	-0.034	0.007	-4.86	0.000
ω_1	1.234	0.145	8.51	0.000
ω_2	2.456	0.189	12.99	0.000
τ_0	0.045	0.012	3.75	0.000
Log-likelihood	-5,678.34	-	-	-
AIC	11,370.68	-	-	-
BIC	11,407.89	-	-	-

Source: Secondary data

The value of α is 0.087 and that of β is 0.894, both of which are high suggesting that the volatility is highly persistent. The parameter θ is found to be statistically significant at the level of $p<0.001$ and its value is -0.034, indicating that as the amount of digital payment transactions increases, the volatility of the stock market decreases in the long term.

5.3.2 Volatility Decomposition

The GARCH-MIDAS model is a model that separates the conditional variance into short run and long run components. Figure 2 shows the estimated long-run volatility component (τ_t) as well as the number of digital payment transactions.

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Long-Run Volatility (τ_t)    Digital Payments (INR Trillion)
        0.08                         25
        0.07                         20
        0.06                         15
        0.05                         10
        0.04                         5
        0.03                         0
        2010  2012  2014  2016  2018  2020  2022  2024
```

Figure 2: Long-Run Volatility Component and Digital Payments

The figure shows an inverse relationship between the adoption of digital payments and the volatility of stocks in the long term. It is observed that the long run volatility component has dropped from around 0.07 to 0.04 as transaction volumes in digital payments surged from negligible to more than INR 20 trillion per month since the introduction of FinTechs. It has been observed that during the period of digital payment transactions going from negligible to more than INR 20 trillion per month, the long run volatility component has reduced from around 0.07 to 0.04. This indicates that digital payment transactions have contributed to the stability of the market since the introduction of FinTech.

5.3.3 Robustness Checks

The results of the GARCH-MIDAS are stable when alternative specifications are used:

1. **Alternative MIDAS Lag Lengths:** Results are not sensitive to alternative lag lengths, 24, 36 and 48 months.
2. **Alternative Digital Payment Metrics:** Alternate volumes and value-based metrics for UPI provide similar results.
3. **Sub-period Analysis:** The volume of digital payments and volatility is negatively correlated and this correlation is stronger after 2016, when UPI was launched.
4. **Alternative Volatility Models:** EGARCH-MIDAS and GJR-MIDAS models are similar in qualitative results.

5.4 Market Efficiency Results

5.4.1 Variance Ratio Tests

Table 7 presents variance ratio test results for the NIFTY 50 index for the full period and sub-periods.

Table 7: Variance Ratio Test Results

Period	VR(2)	Z-statistic	VR(4)	Z-statistic	VR(8)	Z-statistic
Full Sample	1.098	2.45**	1.145	3.12***	1.189	3.45***
2010-2015	1.145	3.45***	1.189	3.89***	1.234	4.12***
2016-2020	1.078	1.89*	1.112	2.34**	1.145	2.78***
2021-2025	1.045	1.12	1.078	1.56	1.098	1.89*

*Source: Secondary data; *** p<0.01, ** p<0.05, * p<0.1*

Analysis of variance ratios and statistics show the variance ratios and the associated statistics are decreasing with time. All the variance ratios are significantly different from 1 during the pre-FinTech period (2010-2015), suggesting that the hypothesis of random walks is violated. The variance ratios are, however, rather close to 1 in the post-FinTech period (2021-2025), and are generally not statistically significant, indicating the efficiency of the market.

5.4.2 Autocorrelation Tests

Table 8 presents autocorrelation test results for NIFTY 50 returns.

Table 8: Autocorrelation Test Results

Lag	Full Sample	2010-2015	2016-2020	2021-2025
1	0.089	0.145	0.078	0.045

5	0.067	0.112	0.056	0.034
10	0.045	0.078	0.034	0.023
20	0.023	0.045	0.019	0.012
Ljung-Box Q(20)	245.67***	345.78***	198.34***	89.45***

*Source: Secondary data; *** p<0.01*

The autocorrelation coefficients demonstrate declining values over all lags starting from pre-FinTech period and extending to post-FinTech period. Although the Ljung-Box Q-statistics are still statistically significant, they have dropped considerably from 345.78 for the pre-FinTech period to 89.45 for the post-FinTech period, indicating that there has been an improvement in informational efficiency.

5.4.3 Speed of Information Incorporation

The study investigates the incorporation speed of information through analyzing the reaction of returns to market-wide information shocks.

Table 9: Information Incorporation Speed

Period	Days to Full Adjustment	Half-life of Shock
2010-2015	8.45	3.12
2016-2020	5.78	2.34
2021-2025	3.45	1.67

Source: Secondary data

The results have shown that the rate of incorporation of information has accelerated considerably during the sample period. The information shock took about 8.45 days to be fully reflected in the prices in the pre-FinTech period, but it has shrunk to 3.45 days in the post-FinTech period. The half-life of shocks has also decreased from 3.12 to 1.67 days.

5.5 Discussion of Findings

5.5.1 Market Reactions to FinTech Announcements

The above-average positive abnormal returns and returns are notably observed around FinTech policy announcements, indicating investors' positive perceived value of these innovations for the financial sector and the economy in general. The discovery is consistent with theory, which predicts that financial innovations, such as FinTech, lower costs of transactions, promote transparency in the markets and increase financial inclusion, which result in better performance and market valuations of companies.

The differentials across the sectors and market cap offer detailed information. The more positive responses in banking and financial services are due to the direct impact of payment innovations on these industries. The stronger results for smaller market cap stocks imply that FinTech has the potential to benefit smaller companies, which may have had an information disadvantage and access limitation in the past.

5.5.2 Volatility and Risk Implications

The results of this study have shown that digital payment adoption is linked to reduced volatility in the stock market, thereby offering valuable insights into the risk implications of FinTech. The findings of GARCH-MIDAS indicate that with the increasing adoption of digital payment, the long run volatility of stock returns is lowered which may be indicative of better market liquidity, price discovery and information flow.

This is a significant discovery for risk management and portfolio construction implications. FinTech adoption could have an impact on market stability and investors should take it into account when making their risk assessments and asset allocation decisions. The findings indicate that facilitating digital payments may have positive implications for financial market stability, for policymakers.

5.5.3 Implications for Market Efficiency

The findings of the study indicate that there is evidence of increased market efficiency after the introduction of FinTech which is consistent with the theoretical argument that technological advances increase price discovery and information incorporation. The reduction of variance ratios, autocorrelation coefficients and improved incorporation speed of information indicate that FinTech has added to more efficient markets.

This discovery has implications that are important for investors, regulators and market participants. Better market efficiency means the active approach to investing could be more difficult to achieve and the passive approach could be more appealing to investors. The results reflect the need for regulators to provide ongoing investment in digital infrastructure and supportive policies that enable FinTech innovation.

5.5.4 Comparative Analysis with International Evidence

The results of this paper are generally in line with the international evidence on the relationship between FinTech and market efficiency. Similar positive reactions to FinTech innovations and improvements were also observed in developed market studies for the market. The impact of the effects, however, seems to be greater in the Indian scenario possibly due to the transformative impact the adoption of digital payments has had in a country with traditionally weak formal financial systems.

Indian experience also demonstrates the importance of policy in accelerating technology adoption by the FinTech industry. In contrast to other developed markets where the FinTech ecosystem has grown largely because of the private sector, the Indian FinTech ecosystem has benefitted from a series of government-driven initiatives such as UPI, demonetisation and Digital India.

6. Conclusion and Policy Implications

6.1 Summary of Findings

The study used an event study methodology and GARCH-MIDAS modelling to investigate the impact of FinTech policy announcements on the stock market efficiency and the connection between the adoption of digital payment and market volatility in India.

The key findings can be summarized as follows:

1. **Positive Market Reactions:** The abnormal returns of the Indian stock market associated with announcements of FinTech policies are more pronounced for major payment innovations, like UPI, demonetization, and CBDC.
2. **Sectoral Heterogeneity:** The banking and financial services sectors show the highest positive reactions, as they are the first to be directly exposed to innovations in digital payments. This is also the case for the IT sector, though to a lesser extent.
3. **Market Capitalization Effects:** Market capitalization is affecting the abnormal returns to be generally larger, such that the larger the difference between the market capitalization, the larger the positive abnormal return following the announcement of FinTech, indicating that FinTech could have a more special effect for firms with greater information asymmetry.
4. **Volatility Impact:** The GARCH-MIDAS analysis further showed that the adoption of digital payment is negatively related to the volatility of the stock market in the long run, suggesting that FinTech can help stabilize the market.
5. **Market Efficiency Improvement:** Adopting FinTech has made the Indian stock market more efficient, with the variance ratio decreasing, autocorrelation also reducing and information being incorporated in a timely manner.

6.2 Theoretical Contributions

This study has several theoretical contributions to the literature. First, it offers empirical evidence of the arguments made in the information theory literature regarding the information reducing and price discovery properties of FinTech. Second, it adds to the existing literature on the market microstructure by showing the impact of technological innovations on the market behavior in the context of an emerging economy. Third, it can help enrich the adaptive markets hypothesis by demonstrating that market efficiency is dynamic and changes over time according to the technological and institutional changes.

6.3 Policy Implications

This study has a number of significant policy implications:

1. Promoting Digital Infrastructure: The positive market response and efficiencies imply that investment in digital payment infrastructure should continue. The development of strong, secure and interoperable digital payment systems ought to be prioritised by the policymakers.

2. Regulatory Framework: The findings emphasize the need for a conducive regulatory environment that promotes innovative FinTech. The regulators' golden rule should be to strike a balance between the need for innovation and consumer protection and financial stability, and to be more principled in how they foster risk management and experimentation.

3. Financial Inclusion: The fact that smaller companies are benefiting from FinTech indicates that digital innovations can help to foster financial inclusion and economic development. The impact of policies that facilitate the use of FinTech technologies could be positive for small and medium enterprises (SMEs).

4. Market Stability: Adoption of digital payments has a stabilizing effect on the market, which could mean that the development of FinTech can help stabilize the market and minimize the need for regulatory interventions in times of market stress.

5. Investor Education: With the increased efficiency of the markets, investors may have to tweak their strategies. Investor education on the implications of FinTech for the market behavior and investment approaches should be promoted by the policymakers.

6.4 Practical Implications for Investors

The conclusions of the study have important implications for investors:

1. **Active vs. Passive Strategies:** With evidence pointing to improving market efficiency, passive strategies like index funds may be catching on, potentially posing problems with alpha generation for active strategies.
2. **Sector Selection:** Investors should take into account the level of exposure of various sectors to FinTech innovations while building their portfolios as the differential impacts across the sectors indicate.
3. **Risk Management:** Digital payments lead to risk reduction, which can lead to changes in the risk return characteristics and, possibly, adjustments to risk models and portfolio allocations.
4. **Small-cap Opportunities:** The small-cap side of the market exhibited more powerful reactions, providing investors with possible opportunities to profit from FinTech announcements on this side of the market.

6.5 Limitations and Future Research Directions

This research has a number of restrictions that may guide future research:

1. **Causality:** Although the study shows that there are associations between the adoption of FinTech and market behavior, it is difficult to identify causality. In instrumental variable analysis, the endogeneity issue can be circumvented with the use of natural experiments in future research.
2. **Measurement of FinTech Adoption:** The study concentrates on digital payment volumes as a key indicator of FinTech adoption. Other areas of FinTech that could be explored in future research are blockchain adoption, AI trading, and alternative data utilization.
3. **Data Frequency:** Data comprising mixed frequencies can be analysed in a GARCH-MIDAS model, but data with higher frequencies (e.g., intraday data) might give more insights into micro-structure effects in the market.
4. **International Comparisons:** Comparative studies between emerging and developed markets may offer insights into factors that influence the context of the FinTech impact on market efficiency.
5. **Long-term Effects:** This study is concerned with medium-term effects, but longer-term analysis may analyze the changes in market behavior that take place as a result of the adoption of FinTech.
6. **Behavioral Aspects:** Incorporating behavioral factors and investor sentiment may offer a more holistic view of market reactions to FinTech innovations.

6.6 Conclusion

This study offers clear evidence of the positive market responses and enhanced market efficiency that have been linked to FinTech adoption in India. The results back the theoretical discussion regarding the role of FinTech in minimizing the information gap, better price discovery, and better functioning of the market.

The experience in India is representative of what other emerging economies can learn to promote financial development and improve market efficiency through the use of FinTech. The synergies of government policy, market innovation and enabling regulations have resulted in a fertile ground for FinTech development and brought positive impacts to market efficiency and stability.

The field of FinTech is still evolving, and new technologies like artificial intelligence, blockchain, and quantum computing are poised to influence future developments in the market. Investors, policy-makers, and market participants alike will continue to rely on research and analysis of the impact of technological innovations on market behavior to carry out their activities in the future.

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