Dynamic Volatility Spillovers Between Banking and Fintech-Related Sectors in India: Evidence from A Tvp-Var Connectedness Approach

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1. Introduction

The rapid expansion of financial technology (FinTech), broadly defined as the application of digital and information technologies to financial services, has significantly transformed modern financial systems (Arner et al., 2016; Gomber et al., 2018). FinTech innovations—such as digital payments, online lending platforms, algorithmic trading, and data-driven financial services—have improved efficiency, expanded financial inclusion, and altered competitive dynamics within the financial sector. In emerging economies like India, FinTech-driven digitalisation has accelerated markedly in recent years, supported by widespread adoption of digital infrastructure and technology-enabled financial services (Reserve Bank of India [RBI], 2022).

FinTech-enabled efficiency and innovation, while it may also cause financial risk and volatility. Technology-driven financial institutions get integrated largely into traditional financial institutions, by which shocks can spread across industries, thereby affecting financial stability (Vives, 2019). Shocks spread differently over short, medium and long-term horizons and recent advancements in the literature on financial connectedness show that volatility spillovers are time varying and affected differently for different frequencies (Baruník & Křehlík, 2018). In this context, volatility spillovers are crucial as increased stress or uncertainty in one area of the financial system can spread to other areas, increasing systemic risk.

Several factors contribute to the interconnectedness between technology-driven industries and the banking sector. First, Payments, lending and wealth management are the areas highly concentrated by FinTech firms, which instigate a competition with the banking industry (Thakor, 2020). Second, the financial technologies developed by technology firms are actively adopted by traditional banks (Gomber et al., 2018). Third, cross-sectoral linkages are strengthened between banks and IT firms due to their strategic collaborations, outsourcing arrangements and technology partnerships. As a result, the effects in the banking sector may spill over to technology-driven financial activities, while technology-sector shocks may also affect banking sector risk dynamics.

India witnessed a rapid advancement in the FinTech activities, yet volatility spillover between FinTech and the banking sector remains underexplored. One of the big challenges faced during the study is the non-availability of the FinTech index, as it is not constructed in India. To address this limitation, the present study employs the NIFTY IT index as a broad proxy for FinTech-related technological activity. While the IT sector extends beyond FinTech alone, it consists of listed firms engaged in digital infrastructure development, software services, and platform technologies that assist financial digitalisation and innovation in India (Reserve Bank of India [RBI], 2022; PwC India, 2024). Accordingly, volatility spillovers involving the IT sector are interpreted as showing the transmission of technology-driven financial shocks, with due caution regarding the proxy-based nature of this approach.

The Indian banking sector occupies a core position in the financial system and is highly affected by macroeconomic conditions, monetary policy actions, and financial market stress. Volatility propagating in the banking sector may therefore transmit to FinTech-related technological activities through expectations, risk perceptions, and portfolio reallocations (Diebold & Yilmaz, 2012). Equally, rapid technological changes and digital disruptions in the FinTech industry may affect banking sector stability as they may influence the banking sector's competitive conditions and operational risk profiles. These bidirectional linkages underscore the importance of examining volatility spillovers between the banking sector and FinTech-related activities within a dynamic empirical framework.

This study contributes to the literature in several ways. First, it provides empirical evidence on volatility spillovers between the Indian banking sector and FinTech-related technological activity using daily data. Second, it applies GARCH-based volatility modelling to capture time-varying risk dynamics, followed by the Diebold–Yilmaz spillover framework to quantify average and directional volatility transmission (Diebold & Yilmaz, 2012). Third, a time-varying parameter VAR (TVP-VAR) approach is employed to examine the evolution of spillovers over time, allowing for state-dependent changes in interconnectedness that static models may fail to capture. Finally, robustness checks using alternative forecast horizons and model specifications are conducted to ensure the stability of the findings.

The study addresses two key research questions: (i) What are the magnitude and direction of volatility spillovers between the banking sector and FinTech-related technological activity in India? (ii) How do these spillovers evolve over time, particularly during periods of heightened market uncertainty? By addressing these questions, the paper aims to enhance understanding of intersectoral risk transmission in an emerging market context and offer insights relevant for investors, regulators, and policymakers concerned with financial stability.

2. Review of Literature

FinTech and Banking Transformation

The integration of technology-driven financial activities into the banking sector has drastically reshaped the industry. Previous studies emphasise FinTech as a technology-enabled innovation that transforms conventional financial services by enhancing efficiency, accessibility, and customer experience. Al-Ajlouni and Al-Hakim (2018) emphasise that banking sectors are challenged by FinTech firms by offering technology-driven alternatives in payments, lending, and financial intermediation, thereby intensifying competition within these sectors. The authors argue that while FinTech improves operational efficiency and inclusion, it also introduces new challenges for banks.

Available literature also suggests the rapid integration of FinTech in the banking industry. Sharma and Sharma (2024) show that due to high convenience, speed and digital accessibility, a large number of bank customers adopt FinTech services. However, their findings also highlight potential risks such as cybersecurity concerns, lack of awareness, and resistance to technological change, indicating that FinTech adoption is uneven across regions and customer groups.

Volatility Spillovers and Sectoral Interdependence

A large body of literature focuses on volatility spillovers across financial markets and sectors. Malik and Hammoudeh (2007) provide early empirical evidence of shock and volatility transmission between oil markets and equity markets, demonstrating that volatility can propagate across asset classes through economic and financial linkages. Their results underline the importance of modelling second-moment dynamics when assessing market interdependence.

Extending this perspective to a sectoral framework, Sahoo and Kumar (2024) examine volatility spillovers among sectors in emerging and developed markets, including the information technology (IT) sector. Their findings reveal significant cross-sector volatility transmission, particularly during periods of heightened uncertainty, with developed market sectors often exerting a dominant influence. This evidence supports the view that sector-level analysis provides deeper insights into financial risk transmission than aggregate market studies.

Systemic Risk, Connectedness, and Financial Contagion

Theoretical and empirical studies emphasise the role of interconnected financial institutions in amplifying systemic risk. Allen and Gale (2000) develop a foundational theoretical model showing how interbank linkages can transmit liquidity shocks across regions, leading to financial contagion even in the absence of aggregate uncertainty. This work establishes the microeconomic foundations of contagion and highlights the fragility of interconnected financial systems.

Building on this theoretical framework, Billio et al. (2012) provide empirical measures of connectedness among financial institutions using principal component analysis and Granger-causality networks. Their results indicate that banks play a central role in transmitting shocks across the financial system, thereby contributing disproportionately to systemic risk. These findings are particularly relevant in the context of increasing integration between traditional banking institutions and technology-driven financial activities.

Methodologically, Dungey et al. (2005) review empirical approaches to modelling financial contagion and demonstrate that different contagion measures often capture similar underlying transmission mechanisms. Their synthesis highlights the importance of choosing appropriate models to distinguish between interdependence and contagion during crisis periods.

Time-Varying and Crisis-Driven Spillovers

Recent studies underscore that volatility spillovers are dynamic and state-dependent. Su and Liu (2021) analyse sectoral volatility spillovers in China and show that spillover structures vary over time and across sectors, particularly during periods of economic policy uncertainty. Their results indicate that shocks affect sectors heterogeneously, reinforcing the need for dynamic modelling approaches.

Similarly, Tian, Alshater, and Yoon (2022) document time-varying risk spillovers from oil markets to stock markets using a GARCH–copula–CoVaR framework. They find that downside spillovers are stronger than upside spillovers, especially during crisis periods, highlighting the asymmetric nature of risk transmission. These findings align with the broader literature that emphasises heightened spillover intensity during financial stress.

Overall, the literature establishes that (i) FinTech is transforming banking operations and competitive dynamics, (ii) financial markets and sectors are interconnected through volatility spillovers, and (iii) banks and financial institutions play a central role in systemic risk transmission. While extensive research exists on volatility spillovers and financial contagion, limited empirical work integrates FinTech-driven sectors—such as information technology—with traditional banking sectors in an emerging market context. This gap motivates the present study to examine dynamic volatility spillovers between banking and technology-driven sectors.

3. Methodology

3.1 Data Description

The dynamic volatility spillovers between the banking and FinTech sectors are examined in this study. Due to data constraints, the listed FinTech companies in India are mostly integrated into the larger Information Technology (IT) sector. Thus, in line with earlier research, the IT sector index is used as a stand-in for FinTech operations. The sectoral indices' daily closing prices are used to record changes in the market during the study period. Traditional financial institutions are represented by the banking sector index, whereas technology-driven financial activity (FinTech) is represented by the IT sector index. By taking the logarithmic first differences of prices, all price series are transformed into continuously compounded returns. In addition to ensuring stationarity, this transformation makes it possible to analyse volatility dynamics effectively.

3.2 Preliminary Analysis

Descriptive statistics, such as mean, standard deviation, skewness, and kurtosis, are calculated to summarise the fundamental characteristics of the return series prior to assessing volatility spillovers. The Jarque-Bera test is used to determine whether returns are normal. Unit root tests are used to verify the return series' stationarity in order to guarantee the applicability of volatility modelling. The ARCH-LM test, which determines whether conditional heteroskedasticity is present in the data, is also used to look for volatility clustering.

3.3 Volatility Estimation

The Generalised Autoregressive Conditional Heteroskedasticity (GARCH) model is used to estimate volatility for each sector. By enabling current volatility to depend on previous shocks and volatility, the GARCH framework captures time-varying volatility. Because it accurately simulates the volatility clustering and persistence frequently seen in financial return series, this method is frequently employed in financial studies. The spillover analysis uses the calculated conditional variances from the GARCH model as inputs.

3.4 Volatility Spillover Measurement

The Diebold-Yilmaz spillover framework is used to investigate volatility spillovers between the banking and FinTech sectors, represented by the IT sectors. Forecast error variance decomposition from a vector autoregression (VAR) model serves as the foundation for this technique. It quantifies the extent to which shocks originating in one sector account for the forecast error variance of another sector. The framework makes it possible to identify spillover transmitters and receivers by providing total, directional, and net spillover indices.

3.5 Time-Varying Spillover Analysis

This study uses a Diebold–Yilmaz connectedness framework based on time-varying parameter vector autoregression (TVP-VAR) to capture the dynamic evolution of volatility spillovers. The VAR coefficients can change smoothly over time because the TVP-VAR model is estimated in a Bayesian state-space form using forgetting factors and Minnesota priors. Without depending on arbitrary rolling-window selection, this method captures slow structural changes in volatility transmission.

3.6 Robustness Tests

Robustness checks are carried out by changing the VAR model's lag length and forecast horizon to guarantee the accuracy of the findings. The robustness of the empirical findings is confirmed by the stability of spillover patterns across different specifications.

4. Empirical Findings

4.1 Descriptive Statistics

H_0 : The returns are normally distributed

Table 1: Descriptive Statistics									
	Mean	SD	Min	Max	Skewness	Kurtosis	JB_Statistic	JB_p Value	Obs
NIFTY IT	0.000763	0.013942	-0.10065	0.086404	-0.42817	8.919413	2581.602255	0	1732
BANK NIFTY	0.000403	0.015084	-0.18313	0.099951	-1.26419	21.90341	26249.30585	0	1732

Table 1 presents the descriptive statistics of daily returns for the NIFTY IT and Bank Nifty indices over the sample period. Both return series exhibit relatively small positive mean returns, which is typical for high-frequency financial data and suggests that risk characteristics, rather than average returns, dominate market behaviour. The standard deviation indicates that the banking sector is more volatile than the IT sector (represented for FinTech), reflecting its greater exposure to macroeconomic and financial shocks. The minimum and maximum values reveal the presence of large negative and positive return realisations, with the banking sector experiencing substantially more severe downside risk.

Additionally, both return distributions have a negative skew, which suggests that extreme negative returns are more likely than positive ones, especially for the banking industry. The strong fat-tailed behaviour and frequent occurrence of dramatic market moves are highlighted by the kurtosis values, which greatly surpass the benchmark of three. In line with these findings, the null hypothesis of normality for both series is severely rejected by the Jarque–Bera test. Overall, our findings support the use of GARCH-type volatility models and time-varying spillover frameworks in further investigation by confirming the existence of volatility clustering, asymmetry, and non-normality in returns.

4.2 Stationarity Test

H_0: The return series has a unit root (non-stationary)

Table 2: Stationarity Test				
	Test	Series	Statistic	P_value
1	ADF	NIFTY IT	-10.4972	0.01
2	ADF	BANK NIFTY	-10.6965	0.01
3	PP	NIFTY IT	-1811	0.01
4	PP	BANK NIFTY	-1761.38	0.01

The results of the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests applied to the daily return series of the NIFTY IT and Bank Nifty indices are shown in Table 2. Under both testing strategies, the null hypothesis of a unit root is firmly rejected for both series at the 1% significance level. These results verify that the return series' values are stationary, meeting the prerequisite for time-varying spillover analysis and volatility modelling.

4.3 ARCH Effects Test

H_0: There are no ARCH effects (homoskedastic variance).

Table 3: ARCH LM TEST				
Series	Lags	Chi_Square	DF	P_value
NIFTY IT	5	301.1758	5	<0.001
BANK NIFTY	5	217.1038	5	<0.001

The null hypothesis that there are no ARCH effects for the NIFTY IT (FinTech) and Bank Nifty return series is severely rejected by the ARCH LM test findings shown in Table 3. Significant conditional heteroskedasticity and volatility clustering in returns are shown by the highly significant test statistics. The use of GARCH-type models to estimate time-varying volatility dynamics is strongly supported empirically by these results.

4.4 Volatility Estimation

Table 4: GARCH (1,1) RESULTS		
Parameter	NIFTY_IT	BANK_NIFTY
mu	0.001018713	0.000626275

omega	9.38E-06	5.25E-06
alpha1	0.071781199	0.125295878
beta1	0.875681489	0.852186783

Table 4 reports the GARCH (1,1) estimation results for the NIFTY IT (FinTech) and Bank Nifty indices. The estimated ARCH and GARCH parameters are positive and economically meaningful for both series, confirming the presence of time-varying volatility. The banking sector exhibits a stronger short-run response to market shocks, as reflected by a higher ARCH coefficient, while the IT sector (FinTech) displays slightly greater volatility persistence. The sum of the ARCH and GARCH coefficients remains close to unity for both indices, indicating highly persistent volatility dynamics. These findings suggest that volatility shocks in both sectors dissipate slowly over time, thereby providing a suitable basis for examining volatility spillovers using time-varying frameworks.

4.5 Spillover Analysis

Table 5: Average Volatility Spillovers (Diebold–Yilmaz)

	VOL_IT	VOL_BANK	FROM
VOL_IT	84.2	15.8	15.8
VOL_BANK	15.01	84.99	15.01
TO	15.01	15.8	30.81
Inc.Own	99.22	100.78	cTCI/TCI
NET	-0.78	0.78	30.81/15.40
NPT	0	1	

The GARCH (1,1) estimation results for the Bank Nifty and NIFTY IT (FinTech) indices are shown in Table 4. For both series, the calculated ARCH and GARCH parameters are positive and economically significant, indicating the existence of time-varying volatility. A higher ARCH coefficient indicates that the banking industry responds to market shocks more strongly in the near term, whereas the IT industry (FinTech) shows somewhat more volatility persistence. For both indices, the sum of the ARCH and GARCH coefficients stays near to unity, suggesting extremely persistent volatility dynamics. These results provide a good foundation for analyzing volatility spillovers using time-varying frameworks since they imply that volatility shocks in both sectors fade gradually over time.

4.6 Time-Varying Volatility Spillovers

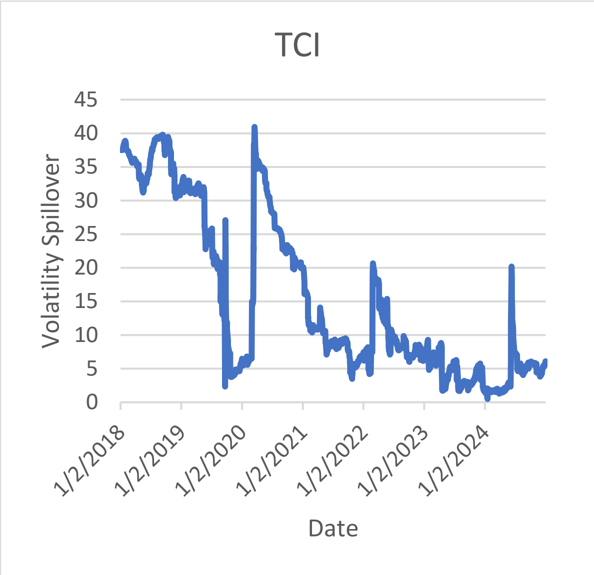

Fig 1:Time-varying Total Spillover Index (TCI)

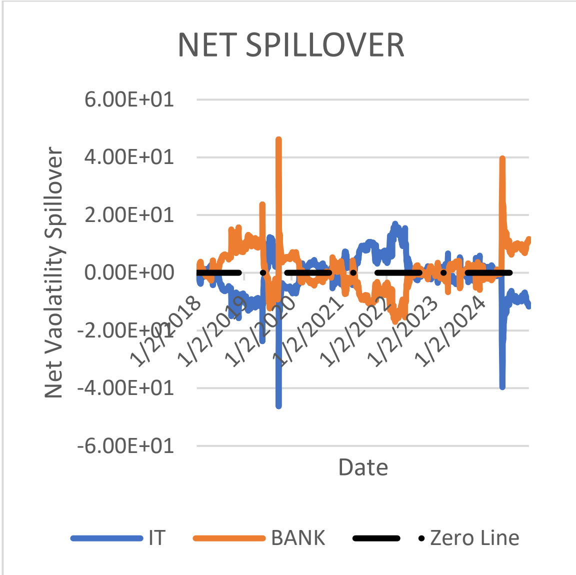

Fig 2: Net Volatility Spillovers Between IT (FinTech) and Banking Sector

The evolution of the time-varying total volatility spillover index (TCI) between the banking and IT (FinTech) sectors, as determined by the TVP-VAR Diebold–Yilmaz framework, is depicted in Figure 1. The findings show that spillover intensity varies significantly over time, suggesting that volatility transmission across sectors is not constant but rather changes in response to shifting market conditions. Relatively low spillover values are associated with calm market periods, indicating that systematic shocks are the main cause of sectoral volatilities under normal circumstances.

On the other hand, when market uncertainty is high, the overall spillover index rises sharply, indicating increased cross-sectoral volatility transmission. These spikes show that shocks that start in one sector quickly spread to the other, increasing systemic risk. The continuation of high spillover levels during these times implies volatility. The persistence of elevated spillover levels during such periods suggests that volatility linkages strengthen and remain elevated until market conditions stabilise.

Figure 2 presents the time-varying net volatility spillovers between the IT (FinTech) and banking sectors. Positive (negative) values indicate that a sector acts as a net transmitter (receiver) of volatility. The results show that the banking sector consistently emerges as a net transmitter of volatility, particularly during periods of elevated total spillovers, while the FinTech represented by the IT sector predominantly functions as a net receiver. This asymmetric transmission pattern becomes more pronounced during stress periods, highlighting the central role of the banking sector in propagating volatility to the Fintech sector (IT sector as proxy).

Overall, the time-varying spillover analysis underscores the state-dependent nature of volatility connectedness between the FinTech represented by the IT sector and the banking sector. While intersectoral spillovers remain moderate during normal periods, they intensify significantly during market stress, emphasising the importance of employing time-varying frameworks to capture dynamic risk transmission mechanisms that static models may fail to detect.

4.7 Robustness Analysis

To assess the robustness of the empirical findings, several additional checks are conducted. First, the volatility spillover analysis is re-estimated using alternative specifications within the TVP-VAR framework by varying the forecast horizon. The results remain qualitatively unchanged, with the total spillover index continuing to exhibit pronounced time variation and elevated spillover levels during periods of market stress. The banking sector consistently emerges as a net transmitter of volatility, while the FinTech proxied by the IT sector remains a net receiver, confirming the stability of the main results.

Second, the robustness of the volatility estimates is examined by considering alternative GARCH specifications. Estimating the conditional volatility using alternative distributional assumptions yields similar volatility dynamics and persistence patterns, indicating that the spillover results are not sensitive to the specific GARCH(1,1) specification adopted in the baseline model.

Overall, these robustness checks confirm that the key findings regarding the magnitude, direction, and time variation of volatility spillovers between the FinTech proxied by the IT and banking sectors are stable across alternative model configurations. This strengthens confidence in the reliability of the reported spillover dynamics and supports the validity of the study's conclusions.

As a robustness check, the TVP-VAR spillover analysis is re-estimated using an alternative forecast horizon. Increasing the forecast horizon from 10 to 20 leads to a modest increase in the average total spillover index; however, the qualitative pattern of spillovers remains unchanged. In particular, the banking sector continues to act as a net transmitter of volatility, while the FinTech (IT sector as proxy) remains a net receiver. These findings confirm that the main results are robust to alternative forecast horizon choices.

5. Discussion and Policy Implications

The empirical results provide important insights into the nature of volatility transmission between the FinTech (IT sector as proxy) and banking sectors in India. The presence of economically meaningful average spillovers, combined with strong time variation in connectedness, suggests that sectoral volatilities are not isolated but dynamically interlinked. In particular, the banking sector consistently emerges as a net transmitter of volatility, while the FinTech (IT sector as proxy) predominantly acts as a net receiver. This asymmetric transmission pattern highlights the central role of the banking sector in propagating systemic risk across sectors.

The dominance of the banking sector as a volatility transmitter can be attributed to its strong exposure to macroeconomic conditions, monetary policy changes, and financial stability concerns. Shocks originating in the banking sector tend to affect broader economic expectations, which in turn influence risk perceptions in the FinTech represented by the IT sector. The amplification of spillovers during periods of market stress further indicates that sectoral diversification benefits weaken when they are most needed, as volatility linkages intensify during crises.

From an investment perspective, the findings imply that portfolio diversification across the FinTech represented by the IT sector and banking sectors may offer limited risk-reduction benefits during periods of heightened uncertainty. Investors should therefore account for time-varying spillovers when designing risk management and hedging strategies, particularly during systemic events when volatility transmission is elevated.

From a regulatory and policy standpoint, the results underscore the importance of monitoring volatility dynamics in the banking sector as a leading indicator of broader market instability. Since banking sector volatility spills over into the FinTech represented by the IT sector, financial stability policies aimed at enhancing banking sector resilience may have positive spillover effects on other sectors of the economy. The use of time-varying connectedness measures can therefore support early-warning systems and contribute to more effective financial stability monitoring.

Overall, the results highlight the need to move beyond static risk assessments and adopt dynamic frameworks that capture evolving intersectoral linkages. By identifying periods of intensified spillovers and dominant volatility transmitters, policymakers and market participants can better anticipate and manage systemic risk.

6. Conclusion

This study analyses volatility spillovers between the FinTech and banking sectors in India using a time-varying connectedness framework over the period 2018–2024. The findings show that while own-sector shocks account for a large share of volatility, cross-sector spillovers are significant and highly time-varying, intensifying during periods of market uncertainty. The banking sector emerges as a net transmitter of volatility, whereas the FinTech sector (proxied by the IT sector) mainly acts as a net receiver, highlighting the central role of banks in intersectoral risk transmission. These results underscore the importance of dynamic spillover analysis for understanding systemic risk and have relevant implications for financial stability monitoring and policy formulation.

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