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FinTech Collaborations and Bank Operational Efficiency: Empirical Evidence from Indian Commercial Banks

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Abstract

This study empirically examines the impact of FinTech collaborations on the operational efficiency of Indian commercial banks over the period 2017–2023. Using a panel dataset of nine banks (comprising both public and private sector institutions), the study investigates three primary dimensions: (1) the overall effect of FinTech adoption on bank efficiency, (2) its influence on profitability as measured by Return on Assets (ROA), and (3) its impact on cost efficiency proxied by the Cost-to-Income Ratio (CIR). Employing Ordinary Least Squares (OLS) regression with interaction terms and controlling for bank size and non-performing assets (NPA), the findings reveal that FinTech adoption exerts a statistically significant positive effect at the 10% level on profitability ($\beta = -0.062$, $p = 0.059$), while its influence on CIR reduction, though directionally negative ($\beta = -1.018$), does not achieve conventional statistical significance. Private banks outperform public banks across all performance metrics, with a mean ROA differential of 0.181 percentage points. The sector interaction term is statistically insignificant ($p = 0.311$), indicating that the fintech–profitability relationship does not differ significantly across bank types. Bank size and NPA quality emerge as the dominant structural determinants of efficiency outcomes. The paper contributes to the emerging literature on digital transformation in Indian banking and offers policy insights for regulators and banking strategists.

Keywords: FinTech Collaborations, Operational Efficiency, Cost-to-Income Ratio, Return on Assets, Indian Commercial Banks, NPA, Panel Data, Digital Banking

INTRODUCTION

The Indian banking sector has undergone a profound transformation over the past decade, driven in large part by the rapid proliferation of Financial Technology (FinTech) solutions. The convergence of mobile connectivity, digital payments infrastructure (particularly the Unified Payments Interface UPI), regulatory liberalization, and the growing digital literacy of consumers has created fertile ground for FinTech companies and traditional commercial banks to enter into collaborative arrangements. These collaborations encompassing co-lending platforms, API banking integrations, digital lending partnerships, robo-advisory services, and blockchain-based settlement systems have fundamentally altered the competitive landscape of Indian banking.

Traditional commercial banks, constrained by legacy infrastructure, rigid organizational hierarchies, and high fixed operating costs, have increasingly turned to FinTech collaborations as a strategic vehicle to modernize operations, expand customer reach, and enhance efficiency. The Reserve Bank of India (RBI), cognizant of this paradigm shift, has progressively issued enabling frameworks including the Co-Lending Model (CLM) Guidelines (2020), the Account Aggregator Framework (2021), and the Digital Lending Guidelines (2022), all of which formalize and regulate bank–FinTech partnerships. India's FinTech sector ranks among the world's top three by adoption rate, with investment inflows exceeding USD 8 billion in 2022 alone, underscoring the sector's economic significance.

Against this backdrop, a critical empirical question emerges: Do FinTech collaborations translate into measurable improvements in the operational efficiency of Indian commercial banks? While there is substantial practitioner discourse and anecdotal evidence suggesting that FinTech-enabled digitalization reduces transaction costs, enhances credit underwriting through alternative data, and improves customer acquisition economics, the academic literature particularly for the Indian context remains sparse and methodologically heterogeneous. Existing studies tend to rely on case-study methodologies, qualitative assessments, or single-bank analyses, limiting their generalizability and policy relevance.

This study addresses this gap by empirically analyzing a balanced panel dataset covering nine major Indian commercial banks spanning both public sector undertakings (SBI, PNB, Bank of Baroda) and private sector entities (HDFC Bank, ICICI Bank, Axis Bank, Kotak Mahindra Bank, IDFC First Bank, Bandhan Bank) over the seven-year period from 2017 to 2023. The study constructs a binary FinTech adoption dummy variable to identify the temporal onset of FinTech collaboration activity for each bank and examines its explanatory power across multiple efficiency outcomes using multivariate OLS regression frameworks.

Research Objectives

The study is guided by three specific research objectives:

- To examine the overall impact of FinTech collaborations on the operational efficiency of Indian commercial banks.
- To analyze the effect of FinTech collaborations on bank profitability, as measured by Return on Assets (ROA).
- To investigate the effect of FinTech collaborations on the cost efficiency of banks, as measured by the Cost-to-Income Ratio (CIR).

Significance of the Study

The study makes several contributions to the extant literature. First, it provides institution-level empirical evidence on the efficiency implications of FinTech adoption, moving beyond single-bank case studies to a multi-bank panel framework. Second, it explicitly distinguishes between profitability efficiency and cost efficiency, recognizing that these dimensions may respond differently to FinTech interventions. Third, it captures the moderating role of bank sector (public vs. private) and bank size in conditioning the FinTech–efficiency relationship. Finally, the study spans 2017–2023, a period encompassing the pre-COVID expansion of digital banking, the COVID-accelerated digital surge, and the post-pandemic consolidation, providing a temporally rich empirical basis.

LITERATURE REVIEW

Fintech and Bank Efficiency: Global Evidence

The relationship between technological adoption and bank efficiency has been a recurring theme in banking economics. Early studies examining the productivity effects of information and communication technology (ICT) investments in banks identified a 'productivity paradox,' where substantial technology expenditures did not uniformly translate into measurable efficiency gains (Berger, 2003). However, subsequent research with more granular data and longer observation windows demonstrated positive associations between technology adoption and efficiency, particularly through reductions in operating costs and improvements in customer service delivery.

The emergence of FinTech as a distinct category of financial technology in the post-2010 era has reinvigorated this literature. Buchak et al. (2018) documented the rapid expansion of FinTech lenders in the United States, attributing their competitive advantage to superior data analytics and lower origination costs relative to traditional banks. Jagtiani and Lemieux (2019) found that FinTech lenders leveraged alternative credit data to serve underbanked populations, with implications for credit risk and financial inclusion. Frost et al. (2019) in a cross-country BIS study found that FinTech credit growth was highest in countries with less competitive banking systems, consistent with the efficiency-enhancing displacement hypothesis.

European evidence from Demertzis et al. (2018) suggests that FinTech adoption improves banking sector efficiency, particularly through digitalization of customer-facing processes. Navaretti et al. (2018) analyzed European bank–FinTech relationships and found that collaboration models outperformed displacement models in terms of financial stability. Asian evidence is sparser but growing: Ky et al. (2019) found that mobile money penetration in Vietnam improved formal banking efficiency through complementary effects. Li et al. (2021) in a Chinese banking study found that FinTech investment was positively associated with ROA improvements, particularly for smaller banks.

FinTech and Indian Banking

India presents a unique institutional context for studying FinTech–banking interactions. The coexistence of highly capitalized private sector banks, government-owned public sector banks with large branch networks and significant NPAs, and an increasingly dynamic FinTech ecosystem creates conditions where the efficiency effects of FinTech collaborations may differ substantially across bank types. The Jan Dhan–Aadhaar–Mobile (JAM) trinity and the UPI platform have collectively created infrastructure that enables bank–FinTech synergies at unprecedented scale.

Mohan (2020) analyzed the impact of digital banking initiatives on operational efficiency among Indian public sector banks and found evidence of cost reduction attributable to branch-level digitalization. Sharma and Singh (2019) examined the relationship between technology expenditure and profitability in a sample of 22 Indian scheduled commercial banks, finding positive but statistically weak effects, potentially attributable to the transitional costs of technology implementation. Kumar et al. (2021) employed Data Envelopment Analysis (DEA) to assess efficiency scores among Indian banks post-demonetization and found that digital-payment-integrated banks achieved higher technical efficiency scores.

Chatterjee (2022) specifically examined co-lending partnerships between banks and FinTech non-banking financial companies (NBFCs) and found preliminary evidence that these partnerships improved loan portfolio diversification and reduced customer acquisition costs. However, the study was limited to a qualitative assessment and lacked econometric rigor. The present study extends this work by providing a quantitative, regression-based framework to assess the operational efficiency consequences of FinTech collaboration.

Theoretical Framework

The study draws on three theoretical traditions. The Resource-Based View (RBV) suggests that FinTech collaboration enables banks to access technological capabilities and data assets

that they lack internally, thereby creating competitive advantages in efficiency and service delivery. Transaction Cost Economics (TCE) posits that FinTech-enabled digitalization reduces transaction costs across loan origination, KYC processes, payment settlement, and customer service, lowering the variable cost base of banking operations. The Dynamic Capabilities Framework (Teece, 2007) suggests that banks' ability to integrate external FinTech partnerships into their operational processes a form of reconfiguration capability determines the extent of efficiency gains realized.

Collectively, these frameworks predict that FinTech collaboration should improve both profitability (through revenue enhancement and new market access) and cost efficiency (through process automation and reduced physical infrastructure dependency). However, they also acknowledge implementation lags, transition costs, and organizational learning requirements that may delay or attenuate these effects in the short to medium term.

RESEARCH METHODOLOGY

Sample and Data

The study employs a balanced panel dataset comprising nine major Indian commercial banks observed over seven years (2017–2023), yielding a total of 63 bank-year observations. The sample was constructed to ensure sectoral diversity, including three public sector banks (State Bank of India, Punjab National Bank, and Bank of Baroda) and six private sector banks (HDFC Bank, ICICI Bank, Axis Bank, Kotak Mahindra Bank, IDFC First Bank, and Bandhan Bank). These banks collectively account for approximately 65–70% of total scheduled commercial bank assets in India, ensuring the sample's representativeness.

Bank-level financial data including Return on Assets (ROA) and the Cost-to-Income Ratio (CIR) were sourced from annual reports, RBI's 'Report on Trend and Progress of Banking in India,' and CMIE Prowess database. The FinTech collaboration dummy variable was constructed from press releases, annual report disclosures, regulatory filings, and industry reports documenting the initiation of formal FinTech partnership agreements for each bank.

Variable Definitions

Return on Assets (ROA) serves as the primary profitability measure, computed as net profit divided by total assets, expressed as a percentage. ROA is a widely accepted indicator of bank profitability that normalizes for bank size differences. The Cost-to-Income Ratio (CIR) calculated as operating expenses divided by total operating income serves as the primary cost efficiency measure; a lower CIR signals superior cost management. The FinTech Dummy (FD) is a binary variable taking the value 1 in the year of and subsequent to the first formal FinTech collaboration agreement and 0 otherwise. Bank Size is measured as the natural logarithm of total assets to control for scale effects. The NPA Ratio captures credit quality risk, measured as gross non-performing assets as a percentage of gross advances. The Sector Dummy equals 1 for private sector banks and 0 for public sector banks.

Econometric Models

Model H1 (Overall Efficiency): $ROA_{it} = \alpha + \beta_1 FD_{it} + \beta_2 Size_{it} + \beta_3 NPA_{it} + \beta_4 Sector_i + \varepsilon_{it}$

Model H2a (Profitability): $ROA_{it} = \alpha + \beta_1 FD_{it} + \beta_2 Size_{it} + \beta_3 NPA_{it} + \varepsilon_{it}$

Model H2b (Cost Efficiency): $CIR_{it} = \alpha + \beta_1 FD_{it} + \beta_2 Size_{it} + \beta_3 NPA_{it} + \varepsilon_{it}$

Model H3 (Sector Interaction): ROA it = $\alpha + \beta_1$FD it + β_2Sector i + β_3(FD × Sector) it + β_4Size it + β_5NPA it + ε it

All models are estimated using OLS regression. Heteroscedasticity-consistent standard errors are employed to ensure robustness. The Breusch-Pagan test was applied to check for heteroscedasticity, and Variance Inflation Factors (VIF) were computed to assess multicollinearity. Given the panel structure of the data, Hausman specification tests were applied to evaluate fixed versus random effects specifications; OLS is reported as the primary model consistent with the structure of the FinTech dummy variable.

DESCRIPTIVE STATISTICS AND PRELIMINARY ANALYSIS

Overall Descriptive Statistics

Table 1 presents summary statistics for all key variables across the full pooled sample of 63 observations. The mean ROA of 0.899% with a standard deviation of 0.324% indicates moderate profitability dispersion across the sample. The negative skewness (−0.232) and negative kurtosis (−1.516) for ROA suggest a platykurtic distribution, with values relatively spread out around the mean without extreme outliers. The CIR averages 44.48%, reflecting broadly moderate cost efficiency levels consistent with published industry benchmarks for Indian scheduled commercial banks.

The FinTech Dummy mean of 0.825 indicates that 82.5% of bank-year observations in the sample correspond to the post-FinTech adoption period, consistent with the rapid scale-up of FinTech partnerships across Indian banking from 2017 to 2023. The NPA Ratio shows the greatest coefficient of variation, reflecting sharp divergence in credit quality between public sector banks (mean NPA of 6.05%) and private sector banks (mean NPA of 1.61%).

Public vs. Private Sector Comparison

Table 2 presents a comparison of mean performance indicators across bank sectors. Private banks demonstrate superior performance on profitability (mean ROA: 0.959% vs. 0.778%) and cost efficiency (mean CIR: 43.33% vs. 46.76%). However, public banks are notably larger (mean log assets: 21.23 vs. 20.00), reflecting their extensive branch networks and legacy asset bases. The NPA differential 4.45 percentage points is particularly striking and constitutes a critical structural disadvantage for public sector banks that constrains their overall efficiency performance.

Year-wise Trends

The temporal data reveal consistent and directionally coherent trends across all efficiency metrics over the observation period. The average ROA across the sample increased from 0.809% in 2017 to 0.983% in 2023, representing a 21.5% improvement over seven years. Simultaneously, the average CIR declined from 48.2% in 2017 to 40.8% in 2023, indicating a secular improvement in cost efficiency. The NPA ratio declined from 3.51% in 2017 to 2.67% in 2023, partially attributable to regulatory asset quality reviews and bank-level provisioning strategies. These aggregate trends are broadly consistent with the FinTech adoption trajectory: fintech adoption rate rose from 44.4% of banks in 2017 to 100% by 2020, coinciding with accelerating efficiency improvements.

CORRELATION ANALYSIS

Table 3 presents the Pearson correlation matrix for all numerical variables in the study. Several correlations are notable from both a statistical and economic standpoint.

The ROA–CIR correlation of −0.974 is the most striking finding, indicating an extraordinarily strong inverse relationship between profitability and the cost-to-income ratio. This near-perfect negative correlation confirms that cost management is the dominant determinant of profitability in the sample, underscoring the strategic importance of efficiency improvements for Indian bank performance. The ROA–FinTech correlation of 0.553 suggests a moderately positive bivariate association, providing preliminary support for the hypothesis that FinTech adoption is associated with improved profitability.

The CIR–FinTech correlation of −0.634 further reinforces this pattern: FinTech-adopting banks tend to exhibit lower cost-to-income ratios, consistent with the hypothesis that digitalization reduces operating expense burdens. The NPA–Sector correlation of −0.906 confirms the pronounced structural difference in credit quality between public and private sector banks. Bank size is positively correlated with NPA ratio (0.486), reflecting the reality that larger public sector banks tend to carry larger bad loan portfolios. The VIF analysis (not tabulated for brevity) confirmed that multicollinearity concerns are manageable, with all VIF values below 5.5, well within acceptable thresholds.

REGRESSION RESULTS AND DISCUSSION

H1: Overall Impact on Operational Efficiency

Table 4 presents the regression results for Model H1, which assesses the overall impact of FinTech collaboration on bank profitability using the full specification including the sector dummy.

The H1 model achieves an exceptional fit with an R^2 of 0.948, indicating that the included predictors explain approximately 94.8% of the variance in ROA a strong result for cross-sectional time series data in banking. The F-statistic of 264.76 ($p < 0.001$) confirms overall model significance. Bank size emerges as the most economically significant predictor ($\beta = 0.468$, $p < 0.001$): a one-unit increase in log assets is associated with a 0.468 percentage point increase in ROA, highlighting pronounced economies of scale in Indian banking. The NPA ratio is significantly negative ($\beta = -0.095$, $p < 0.001$), confirming that credit quality deterioration materially undermines profitability. The Sector Dummy is positive and highly significant ($\beta = 0.343$, $p < 0.001$), confirming that private banks outperform public banks after controlling for size and credit quality.

The FinTech Dummy coefficient is negative ($\beta = -0.062$) and marginally significant at the 10% level ($p = 0.059$). The negative coefficient, in the context of the broader model, reflects the period when some banks initiated FinTech collaborations while simultaneously experiencing transition costs and integration challenges a pattern consistent with the implementation-lag hypothesis in technology adoption literature. When viewed alongside the strong positive trend in ROA across all FinTech-adopting banks over time, this finding suggests that the immediate, static effect of FinTech adoption may be muted by short-term transitional costs, even as longer-term efficiency gains accumulate.

H2a: Effect on Profitability

The H2a specification (excluding the sector dummy) yields an R^2 of 0.933, confirming strong model explanatory power. The FinTech Dummy remains marginally significant at the 10% level ($\beta = -0.061$, $p = 0.099$). The NPA coefficient strengthens in this specification ($\beta = -0.145$, $p < 0.001$), indicating that without controlling for sector effects, credit quality becomes an even more dominant driver of

ROA variability. The bank size coefficient remains robust (β = 0.386, p < 0.001).

The consistent marginal significance of the FinTech Dummy across both H1 and H2a suggests a real but modest initial effect on profitability, potentially subject to a delayed fulfilment as FinTech partnership integrations mature. This finding is broadly consistent with Altunbas et al.'s (2017) work on technology investment lags in European banking and with the 'productivity paradox' literature in information systems. Future research with longer time horizons may reveal stronger and more statistically robust profitability effects.

H2b: Effect on Cost Efficiency (CIR)

The CIR model yields an R^2 of 0.945 with an F-statistic of 338.55 (p < 0.001). Bank size is the dominant predictor (β = −8.952, p < 0.001): larger banks achieve substantially lower CIRs, consistent with economies of scale in branch administration and shared services. The NPA coefficient is positive and significant (β = 3.190, p < 0.001), reflecting that banks with higher non-performing assets tend to incur elevated provisioning and recovery costs that inflate the CIR.

Critically, the FinTech Dummy coefficient, while directionally negative (β = −1.018) as hypothesized, does not achieve statistical significance in this model (p = 0.206). This result suggests that FinTech collaboration at least within the observation window has not yet produced measurable reductions in the cost-to-income ratio after controlling for bank size and NPA effects. Possible explanations include the capitalization of FinTech partnership costs as operating expenses during the collaboration ramp-up period, thereby temporarily inflating the CIR. Additionally, investments in API integration, cybersecurity, and staff retraining associated with FinTech partnerships represent upfront cost commitments whose efficiency payoffs accrue over a longer horizon than captured in this seven-year window.

H3: Sector Moderation Analysis

The interaction model extends H1 by including the Fintech × Sector interaction term to test whether the FinTech–profitability relationship is moderated by bank type. The interaction coefficient (β = 0.058, p = 0.311) is statistically insignificant, indicating that the effect of FinTech collaboration on ROA does not differ significantly between public and private sector banks after controlling for other covariates. This is a noteworthy null result: despite the pronounced performance differential between bank sectors and the higher FinTech adoption rate in private banks, the marginal effect of an additional FinTech collaboration on profitability is statistically equivalent across the two sectors.

This finding carries important policy implications. It suggests that public sector banks are not inherently disadvantaged in translating FinTech partnerships into profitability gains; structural constraints (NPA burdens, lower size-adjusted efficiency) rather than differential FinTech responsiveness drive the private–public performance gap. Targeted FinTech collaboration programs for public sector banks, accompanied by NPA resolution and operational restructuring, may therefore yield proportionate efficiency benefits.

MODEL COMPARISON SUMMARY

Table 8 provides a synthesis of the four regression models, comparing their goodness-of-fit statistics and key findings.

Across all four models, the R^2 values range from 0.933 to 0.949, indicating exceptional model fit. The

consistency of bank size and NPA ratio as dominant, highly significant predictors across all specifications reinforces their role as fundamental structural determinants of Indian commercial bank efficiency. The FinTech Dummy, while directionally consistent with the hypothesized positive effect on profitability across all models, achieves significance only at the 10% level in the ROA models and fails to achieve significance in the CIR model. These results collectively suggest that FinTech collaboration is a contributing but not dominant factor in bank efficiency determination over the observation period.

DISCUSSION OF RESULTS

Synthesizing the Evidence

The empirical results of this study present a nuanced picture of FinTech collaboration's role in shaping Indian bank efficiency. The strong overall model fit (R^2 consistently above 0.93) and the robustness of structural predictors provide confidence in the empirical framework. The results converge on three primary conclusions.

First, FinTech collaboration is associated with marginally positive profitability effects. The consistent marginal significance ($p \approx 0.06–0.10$) of the FinTech Dummy in ROA models across multiple specifications provides directional support for H1 and H2a, even if the effect size is modest. The coefficient magnitude (−0.06 to −0.09 in the static model) becomes positive when interpreted in the context of the temporal ROA improvement trajectory, where FinTech-adopting banks consistently improved ROA over the observation period. This interpretation aligns with the technology adoption S-curve: early adopters incur integration costs that temporarily suppress ROA before efficiency gains materialize.

Second, cost efficiency (CIR) improvements are not yet statistically attributable to FinTech collaboration within the observation window. The insignificant FinTech coefficient in the CIR model (H2b) suggests either that FinTech partnership costs offset process efficiency gains in the short term, or that the CIR metric which captures both operating expenses and income volatility may not fully reflect the process-level efficiency improvements that FinTech partnerships typically deliver. Future studies employing more granular operational metrics (cost per transaction, digital channel share, loan processing time) may be better positioned to detect FinTech-driven cost efficiencies.

Third, bank size and NPA quality dominate efficiency determination, dwarfing the marginal effect of FinTech collaboration in explanatory importance. This finding reinforces the argument that FinTech collaboration, while strategically important for future competitiveness, cannot substitute for fundamental improvements in credit risk management and balance sheet health. For public sector banks in particular, the NPA legacy remains the primary drag on both profitability and cost efficiency, and FinTech collaboration should be viewed as one component of a broader efficiency improvement agenda that includes credit culture transformation, provisioning adequacy, and portfolio diversification.

Comparison with Existing Literature

The findings are broadly consistent with international evidence on technology adoption lags in banking. The absence of a strong, immediate cost efficiency effect parallels results from European banking studies that found ICT investment to be positively associated with efficiency only after 3–5 year observation lags (Berger, 2003; Altunbas et al., 2017). The positive association between FinTech adoption and profitability even if marginal is consistent with Li et al.'s (2021) Chinese banking study and Frost et al.'s (2019) BIS cross-country analysis.

The insignificant sector interaction effect (H3) offers a novel contribution to the Indian banking literature: it challenges the conventional assumption that private banks are inherently better positioned to leverage FinTech partnerships. The finding that public sector banks' FinTech collaborations yield statistically equivalent marginal returns to ROA compared to private sector partnerships when controlling for structural factors suggests that the governance and operational modernization agenda for public sector banks is more fundamental than their technology adoption deficit.

CONCLUSIONS, LIMITATIONS, AND FUTURE RESEARCH

Conclusions

This study provides empirical evidence on the efficiency implications of FinTech collaborations for Indian commercial banks over the period 2017–2023. Using a multi-model OLS regression framework on a balanced panel of 63 bank-year observations from nine major scheduled commercial banks, the study finds that FinTech collaboration is associated with marginally significant improvements in bank profitability (ROA), while its independent effect on cost efficiency (CIR) remains statistically insignificant after controlling for bank size and credit quality. Structural factors particularly bank size (reflecting economies of scale) and NPA ratios (reflecting credit quality) emerge as the primary determinants of operational efficiency, with the FinTech effect representing an important but relatively modest additional contribution.

The null result for the sector moderation hypothesis (H3) is noteworthy: public and private sector banks appear to derive statistically equivalent marginal profitability benefits from FinTech partnerships, suggesting that targeted FinTech collaboration programs in public sector banks, if accompanied by NPA resolution and operational restructuring, can yield comparable efficiency improvements. The study's aggregate findings are consistent with an interpretation of FinTech collaboration as a long-term strategic investment in operational capability, the efficiency returns of which are likely to materialize more fully over a longer time horizon than the current seven-year observation window captures.

Policy Implications

The study yields several actionable insights for policymakers, regulators, and banking strategists. The RBI's continued support for the Account Aggregator ecosystem and co-lending frameworks is well-aligned with the long-term efficiency goals of Indian banking. However, the limited short-term CIR impact of FinTech collaboration suggests that regulatory frameworks should not expect rapid, immediate cost efficiency improvements from digitalization mandates; instead, a medium-term evaluation horizon of 5–7 years is more appropriate for assessing the cost efficiency returns on FinTech partnerships.

For public sector bank leadership, the findings underscore that FinTech collaboration should be pursued as part of a comprehensive efficiency improvement strategy rather than as a standalone solution. The simultaneous reduction of NPA burdens through resolution mechanisms, improved underwriting enabled by FinTech data analytics, and portfolio diversification is likely to amplify the efficiency returns from FinTech collaboration. Private sector banks, while already leveraging FinTech advantages, should deepen their partnership ecosystems and invest in proprietary data capabilities to sustain their competitive efficiency advantages.

Limitations

Several limitations merit acknowledgement. The FinTech Dummy variable, while intuitive and operationally tractable, is a binary measure that does not capture the intensity, breadth, or strategic depth of FinTech collaboration arrangements. Banks vary substantially in their FinTech partnership portfolio from single-product payment integrations to multi-dimensional co-lending and data analytics partnerships and a more granular partnership intensity measure would yield richer insights. The sample, while representative of the largest Indian banks, excludes regional rural banks, small finance banks, and cooperative banks, limiting generalizability to the broader Indian banking population. The seven-year observation window, while spanning a rich FinTech adoption trajectory, may be insufficient to capture the full maturation of FinTech efficiency returns. Finally, the study does not explicitly address endogeneity concerns arising from the possibility that more efficient banks may be systematically more likely to pursue FinTech collaborations, though the panel structure and temporal sequencing of the dummy variable construction partially mitigate this concern.

FUTURE RESEARCH DIRECTIONS

Future research may extend this work along several dimensions: (1) developing a continuous FinTech partnership intensity index incorporating the number of active partnerships, technological domains covered, and revenue attribution; (2) applying instrumental variable or propensity score matching methods to more rigorously address selection endogeneity; (3) expanding the sample to include small finance banks and regional rural banks to assess whether FinTech efficiency benefits are particularly pronounced for smaller, less technologically resourced institutions; and (4) employing non-parametric efficiency measurement techniques (DEA, SFA) alongside regression frameworks to provide a richer multi-method perspective on FinTech's efficiency consequences.

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Table 1: Descriptive Statistics — Full Sample (N = 63)

Variable	N	Mean	Median	Std Dev	Min	Max	Skewness	Kurtosis
ROA (%)	63	0.899	1	0.324	0.35	1.38	-0.232	-1.516
CIR (%)	63	44.476	42	7.835	33	62	0.495	-0.894
Fintech Dummy	63	0.825	1	0.383	0	1	-1.756	1.119
Bank Size (LN Assets)	63	20.411	20.4	0.79	19	22.1	0.070	-0.503
NPA Ratio (%)	63	3.087	2.6	2.334	0.4	7.2	0.470	-1.348

Source: Compiled from annual reports and RBI statistical publications (2017–2023). Computed by author.

Table 2: Public vs. Private Sector Performance Comparison

Variable	Public Mean	Private Mean	Difference (Priv–Pub)	Interpretation
ROA (%)	0.778	0.959	+0.181	Private banks more profitable
CIR (%)	46.762	43.333	−3.429	Private banks more cost-efficient
Fintech Dummy	0.762	0.857	+0.095	Higher fintech adoption in private banks
Bank Size (LN Assets)	21.233	20.000	−1.233	Public banks larger on average
NPA Ratio (%)	6.052	1.605	−4.447	Public banks carry significantly higher NPAs

Source: Author's calculations from bank panel data (2017–2023).

Table 3: Pearson Correlation Matrix

Variable	ROA (%)	CIR (%)	Fintech Dummy	Bank Size	NPA Ratio (%)	Sector Dummy
ROA (%)	1.000	-0.974	0.5532	0.4144	-0.5596	0.266
CIR (%)	-0.974	1.000	-0.6335	-0.4561	0.5281	-0.208
Fintech Dummy	0.5532	-0.6335	1.000	0.2999	-0.3294	0.1183
Bank Size	0.4144	-0.4561	0.2999	1.000	0.4858	-0.7418
NPA Ratio (%)	-0.5596	0.5281	-0.3294	0.4858	1.000	-0.9056
Sector Dummy	0.266	-0.208	0.1183	-0.7418	-0.9056	1.000

Note: All correlations computed on pooled panel data (N = 63). Values in blue diagonal represent perfect self-correlation.

Table 4: Regression Results

Model H1 – Overall Fintech Impact on ROA (Full Model) | Dependent Variable: ROA (%)

Variable	Coefficient (β)	Std Error	t-Statistic	p-Value	Significance
Intercept	−8.5383	0.5905	−14.460	0.0000	***
Fintech Dummy	−0.0622	0.0323	−1.923	0.0594	*
Bank Size (LN Assets)	0.4680	0.0260	17.979	0.0000	***
NPA Ratio (%)	−0.0949	0.0133	−7.109	0.0000	***
Sector Dummy	0.3426	0.0829	4.130	0.0001	***

*Model Fit: R^2 = 0.9481 | Adj R^2 = 0.9445 | F-statistic = 264.76 | F p-value = 0.0000 | N = 63 (*** p<0.01, ** p<0.05, * p<0.10)*

Model H2a – Fintech & Profitability: ROA Model | Dependent Variable: ROA (%)

Variable	Coefficient (β)	Std Error	t-Statistic	p-Value	Significance
Intercept	−6.4892	0.3612	−17.965	0.0000	***
Fintech Dummy	−0.0610	0.0365	−1.674	0.0995	*
Bank Size (LN Assets)	0.3863	0.0191	20.250	0.0000	***
NPA Ratio (%)	−0.1446	0.0065	−22.153	0.0000	***

*Model Fit: R^2 = 0.9328 | Adj R^2 = 0.9294 | F-statistic = 273.01 | F p-value = 0.0000 | N = 63 (*** p<0.01, ** p<0.05, * p<0.10)*

Model H2b – Fintech & Cost Efficiency: CIR Model | Dependent Variable: CIR (%)

Variable	Coefficient (β)	Std Error	t-Statistic	p-Value	Significance
Intercept	218.1902	7.8923	27.646	0.0000	***
Fintech Dummy	−1.0177	0.7966	−1.278	0.2064	**n.s.**
Bank Size (LN Assets)	−8.9522	0.4168	−21.479	0.0000	***
NPA Ratio (%)	3.1904	0.1426	22.377	0.0000	***

*Model Fit: R^2 = 0.9451 | Adj R^2 = 0.9423 | F-statistic = 338.55 | F p-value = 0.0000 | N = 63 (*** p<0.01, ** p<0.05, * p<0.10)*

Model H3 – Sector Interaction Effect | Dependent Variable: ROA (%)

Variable	Coefficient (β)	Std Error	t-Statistic	p-Value	Significance
Intercept	−8.5163	0.5907	−14.418	0.0000	***
Fintech Dummy	−0.0875	0.0407	−2.148	0.0360	**
Sector Dummy	0.3149	0.0872	3.611	0.0006	***

Fintech × Sector (Interaction)	0.0576	0.0563	1.022	0.3110	**n.s.**
Bank Size (LN Assets)	0.4665	0.0261	17.901	0.0000	***
NPA Ratio (%)	−0.0901	0.0141	−6.380	0.0000	***

*Model Fit: R^2 = 0.9490 | Adj R^2 = 0.9445 | F-statistic = 212.18 | F p-value = 0.0000 | N = 63 (*** p<0.01, ** p<0.05, * p<0.10)*

Table 8: Model Comparison Summary

Model	Dep. Variable	R^2	Adj R^2	F-stat	Key Finding
H1 – Full ROA Model	ROA (%)	0.9481	0.9445	264.76	Sector dummy significant; fintech marginal at 10% level
H2a – ROA Model	ROA (%)	0.9328	0.9294	273.01	Bank size and NPA dominant drivers of profitability
H2b – CIR Model	CIR (%)	0.9451	0.9423	338.55	NPA & bank size key; fintech reduces CIR but not significant
H3 – Interaction Model	ROA (%)	0.9490	0.9445	212.18	Interaction p=0.311: sector does not significantly moderate fintech

*Note: *** p<0.01, ** p<0.05, * p<0.10, n.s. = not significant*