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The RegTech Paradox: Balancing Compliance Costs and Digital Synergies in Indian Banking

Daljit Singh

daljitusfs.rsh@gndu.ac.in

Guru Nanak Dev University

Sonia Kundra

Guru Nanak Dev University

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Abstract

This study empirically investigates the impact of regulatory technology (RegTech) adoption on the financial performance of Indian commercial banks. Utilizing a comprehensive panel dataset of 32 listed banks from 2016 to 2025, the research employs Python-based text-mining techniques on published annual reports to construct a novel RegTech adoption index, which is bifurcated into Core Regulatory Technology and RegTech Enabling Technology. To account for the dynamic persistence of bank profitability and resolve potential endogeneity issues, the study utilizes a two-step System GMM estimator alongside baseline Random Effects modeling. The empirical results reveal a significant asymmetrical relationship. Investments in RegTech Enabling Technology such as artificial intelligence and big data yield a strong, positive, and statistically significant enhancement to the Return on Assets (ROA). Conversely, Core Regulatory Technology dedicated strictly to automated compliance acts primarily as a mandatory operational safeguard, demonstrating a statistically insignificant impact on overall profitability. Furthermore, heterogeneity analysis uncovers that the financial benefits of foundational enabling technologies are heavily concentrated among large institutions and private sector banks, whereas the substantial capital expenditures required for core compliance systems actively compress the asset returns of large banks. These core findings are rigorously validated through extensive robustness checks, including the use of alternative dependent variables (ROE), lagged effects, outlier removal, and a Monte Carlo placebo test. Ultimately, this research provides vital strategic insights for bank management and policymakers regarding the operational costs and monetization potential of digital compliance infrastructures.

Keywords: RegTech, Regulatory Technology, Financial Performance, Bank Performance, Bank Profitability

1. Introduction

Over the past decade, the global financial services industry has experienced an unprecedented wave of digital transformation, fundamentally altering how commercial banks operate, compete, and deliver value (Gomber, 2017; Thakor, 2020). Concurrently, the aftermath of the 2008 Global Financial Crisis and subsequent macroeconomic shocks have ushered in an era of stringent, complex, and high-frequency regulatory mandates. To navigate this dual pressure of digital modernization and regulatory compliance, financial institutions have increasingly turned to Regulatory Technology, or "RegTech" (Charoenwong et al., 2024; Teichmann et al., 2023). Broadly defined, Regulatory technology (RegTech) has emerged as a crucial sub-sector of FinTech, offering indispensable solutions to modern compliance challenges. Common applications of RegTech include regulatory sandboxes, accelerators, and innovation hubs (Anagnostopoulos, 2018). Rather than merely patching the flaws of traditional regulatory frameworks, RegTech empowers financial institutions with the dynamic capabilities necessary to adapt to continuous regulatory changes. Ultimately, it acts as a pivotal mechanism for driving regulatory efficiency and anchoring the stability of the financial system (Liu et al., 2024;

Muganyi et al., 2022). It leverages advanced digital infrastructures such as artificial intelligence (AI), machine learning (ML), and big data analytics to streamline compliance execution, enhance fraud detection, and optimize enterprise risk management (Thakor, 2020).

While the adoption of RegTech has surged globally, its financial implications for commercial banks remain theoretically ambiguous and empirically under-explored, particularly within emerging economies. In India, the commercial banking sector serves as the backbone of national economic growth and has recently undergone aggressive digitization, spurred by rapid technological penetration and systemic shifts toward digital finance (Prajapat et al., 2026). However, Indian banks also operate under the rigorous oversight of the Reserve Bank of India (RBI), requiring massive capital expenditures to maintain complex, automated compliance systems. A critical strategic dilemma thus emerges: do these mandated investments in regulatory technology genuinely enhance a bank's financial performance, or do they merely act as costly operational frictions necessary for institutional survival?

This paper offers three significant marginal contributions in comparison to existing research:

Initially, we broaden the existing literature concerning the economic consequences of bank RegTech. While prior studies predominantly treat digital financial investments as a single monolithic entity (Xia et al., 2026), we theoretically and empirically disentangle RegTech into two distinct dimensions: Core Regulatory Technology and RegTech Enabling Technology. Grounded in the Resource-Based View (RBV) of the firm, we hypothesize that RegTech investments possess a dual nature. We posit that foundational digital architectures (*RegTech Enabling Technology*) create operational synergies that enhance overall profitability, whereas systems dedicated strictly to automated reporting and compliance execution (*Core Regulatory Technology*) function primarily as necessary, but costly, operational frictions.

Second, we enrich the methodological measurement of bank RegTech. Much of the existing literature focuses on conceptual business models or provides qualitative assessments of RegTech's potential benefits and implementation challenges (Grassi & Lanfranchi, 2022; Jeyasingh, 2023; Teichmann et al., 2023; Von Solms, 2021). Rigorous quantitative research is exceedingly rare, primarily because there are no standardized financial databases that track RegTech adoption at the institutional level.

Thirdly, we utilize advanced Python-based text-mining techniques on the unstructured data of annual reports. This allows us to construct a comprehensive, standardized, and continuous RegTech adoption index, providing a more accurate quantitative measurement for empirical research.

2. Literature review and hypothesis development

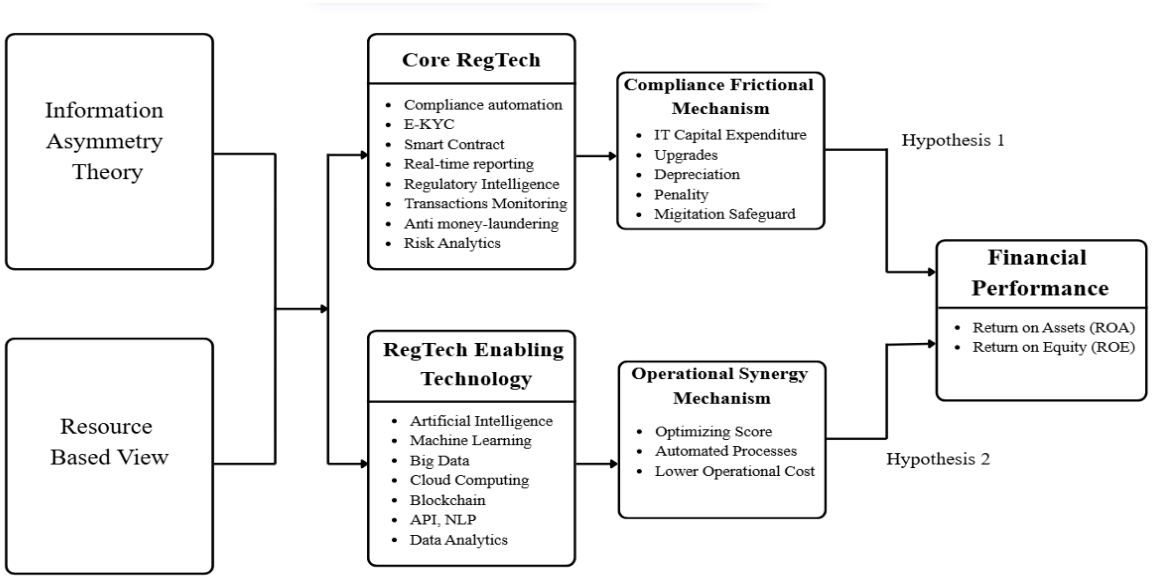
2.1 Theoretical background

2.1.1. Information asymmetry and the RegTech

Beyond internal resource dynamics, the strategic value of RegTech can be fundamentally explained through the lens of Information Asymmetry Theory (Li et al., 2025). In traditional financial markets, profound information asymmetry exists between banks and their borrowing

firms, which prevents banks from accurately assessing a firm's true financial condition, capital structure, and debt repayment ability (Healy & Palepu, 2001). This structural lack of transparency often forces banks to rely on precautionary measures such as elevated lending thresholds or reduced loan volumes which simultaneously intensify corporate financing constraints and limit the bank's own investment efficiency and profitability (Krishnaswami & Subramaniam, 1999). The widespread application of bank RegTech provides a highly effective technological mechanism for overcoming this asymmetry (Dell'Ariccia & Marquez, 2004). By deploying advanced Big Data analytics, machine learning algorithms, and multidimensional data mining, RegTech enables banks to comprehensively and accurately collect and analyze massive amounts of corporate data, including digital footprints and real-time transaction records. This swift access to transparent information streamlines the loan approval process, sharpens the precision of risk assessments, and mitigates operational and Investment vulnerabilities (Li et al., 2025; Teichmann et al., 2023; Wang & Chen, 2024). Furthermore, RegTech serves a critical role in addressing the parallel information asymmetry that exists between regulatory authorities and the banking sector itself. Core compliance technologies such as automated transaction monitoring and machine-readable regulatory reporting alleviate potential conflicts of interest, diminish compliance risks, and ensure systemic stability by seamlessly transmitting verifiable, real-time data to supervisors (Li et al., 2025; Xia et al., 2026), as shown in figure 1

Figure 1 Theoretical framework of the impact of bank RegTech on bank's financial performance



2.1.2. Resource based view and the RegTech

The Resource-Based View (RBV) of the firm provides a compelling theoretical framework for analyzing the strategic implications of RegTech in commercial banking (Anagnostopoulos, 2018; David-West et al., 2018). Traditionally, compliance expenditures in banking have been viewed as defensive, non-revenue-generating operational overhead mandated by supervisory bodies (Charoenwong et al., 2024). However, the RBV shifts this paradigm by conceptualizing technology-enabled compliance not merely as a regulatory safeguard, but as a dynamic bundle

of valuable, rare, inimitable, and non-substitutable organizational capabilities. While standardized compliance execution tools are universally adopted across institutions, foundational digital architectures such as artificial intelligence (AI), machine learning, and big data analytics represent heterogeneous, firm-specific resources that can be embedded deeply across banking operations (Mikalef et al., 2020; Teichmann et al., 2023; Wamba-Taguimdje et al., 2020).

Within this theoretical tradition, researchers increasingly argue that digital financial technologies function as cross-functional resources capable of driving operational synergy (David-West et al., 2018). Foundational RegTech systems generate significant positive spillovers into non-compliance operations by establishing advanced data architectures that reduce transaction frictions, automate backend workflows, and refine predictive credit scoring models. By rendering high-quality data infrastructure a sunk investment, banks can deploy complementary customer relationship and risk analytics tools at lower marginal costs, optimizing cost-to-income efficiency and expanding profit margins (Charoenwong et al., 2024; Zhai et al., 2022). Consequently, the RBV provides a theoretically coherent foundation for evaluating how commercial banks leverage complex digital compliance resources to achieve superior operational efficiency and sustained competitive performance (Anagnostopoulos, 2018; Zhai et al., 2022).

2.1.3. Technology disruption and the shift toward digital banking

The rapid proliferation of financial technology has fundamentally reshaped the competitive landscape of the global banking sector. The exponential growth of external FinTech firms introduces severe competitive disruption, compelling traditional financial institutions to adapt rapidly to prevent the substitution of their core intermediation services. To maintain market share and generate sustained competitive advantages, commercial banks have increasingly internalized digital transformation (Naser et al., 2024; Phan et al., 2020).

2.1.4. Regulatory technology and bank performance

The empirical literature examining the nexus between regulatory technology and commercial bank performance reveals a dual-mechanism impact on profitability metrics like Return on Assets (ROA). The implementation of specialized digital compliance infrastructure, or Core Regulatory Technology, does not universally guarantee immediate financial outperformance. Implementing mandated systems for Anti-Money Laundering (AML) demands massive initial capital expenditures and extensive structural reallocation (X. Chao et al., 2022; Teichmann et al., 2023). Consequently, banks often experience heavy initial cost frictions and time lags before realizing the financial benefits of their digital investments. During these transitional periods, the substantial financial and operational trade-offs required to resolve system errors, train personnel, and upgrade networks can temporarily depress bank profitability (Almulla & Aljughaiman, 2021). Maintaining universal regulatory architectures frequently functions more as a structural cost burden than a revenue generator, requiring banks to fundamentally restructure non-compliance operations to integrate these mandates smoothly.

H_1**:** *Core Regulatory Technology functions primarily as a compliance cost friction, leading to a non-positive or return-compressing effect on overall bank profitability.*

Conversely, when broader digital enabling technologies such as big data analytics, artificial intelligence, and cloud computing are successfully integrated into a bank's core operational architecture, they exert a statistically significant positive effect on structural profitability. By streamlining back-office operations, automating risk management workflows, and expanding digital channels, these technologies actively enhance asset quality and boost overall operational efficiency (N. Chao et al., 2024; Iatzaz Ul Hassan et al., 2025; Lee et al., 2023; Von Solms, 2021). Integrating these versatile systems into strategic management functions, such as a bank's Treasury department, ensures that commercial and prudential objectives are aligned, allowing institutions to process data rapidly while reducing marginal transaction costs (Das, 2025; Goel & Kashiramka, 2026). Consequently, foundational digital integration acts as a direct driver of financial performance by resolving structural information asymmetries and optimizing credit allocation.

H_2**:** *RegTech Enabling Technology exerts a statistically significant positive impact on the financial performance of commercial banks.*

Finally, the translation of RegTech investments into financial performance is highly asymmetrical, heavily moderated by institutional characteristics. The positive effects of digital transformation are often more pronounced in commercial banks with larger asset bases, as these institutions possess the economies of scale necessary to seamlessly absorb high fixed IT costs without compromising their bottom line (Goel & Kashiramka, 2026). Moreover, a bank's ownership structure plays a critical role in its strategic agility; private and state-owned institutions exhibit differing capacities to integrate and monetize digital innovations, directly influencing the magnitude of technological impact on their ROA (N. Chao et al., 2024; Nguyen-Thi-Huong et al., 2023). The remainder of this paper is structured as follows: Section 3 outlines the data sources, variable construction, and the dynamic panel methodology. Section 4 presents the econometric results, including heterogeneity analysis and robustness checks. Finally, Section 5 concludes the study and discusses the strategic implications for commercial banks and regulatory authorities.

3. Data and variables

3.1 Sample and data sources

This study analyzes a comprehensive sample of 32 commercial banks listed on the Indian stock market over a ten-year period from 2016 to 2025. This sample is highly representative of the sector, as these institutions accounted for approximately 95% of the total assets within the Indian banking industry by the end of 2025. To construct the dataset, we gathered information from three primary sources: bank-specific financial data was retrieved from the CMIE ProwessIQ database, technological data and keyword frequencies were extracted directly from the banks' published annual reports, and relevant macroeconomic indicators were sourced from the World Bank database.

3.2 Variables

3.2.1 Explained Variable

Prior literature employs various metrics to evaluate the financial performance of banking institutions, with Return on Assets (ROA) and Return on Equity (ROE) serving as the most widely adopted proxies (Kharrat et al., 2024; Nguyen-Thi-Huong et al., 2023). Aligning with these established methodological conventions, this study adopts ROA as the primary measure of commercial bank financial performance. It is calculated as the ratio of net profit to total assets. This metric provides a highly accurate reflection of managerial efficiency, indicating how effectively a bank utilizes its asset base to generate earnings Additionally, ROE is introduced as an alternative dependent variable to rigorously validate the empirical findings during robustness testing.

3.2.2 Explanatory Variable (Bank RegTech)

Due to the emerging nature of regulatory technology (RegTech) within financial research, a consensus on how to accurately quantify institutional adoption remains absent from the literature. To bridge this methodological gap, this study utilizes text-mining techniques to extract latent strategic information from the unstructured data of commercial banks. Annual reports serve as the optimal primary source for this analysis, as they formally document a bank's technological investments, developmental strategies, and operational priorities. Aligning with the framework established by (Li et al., 2025; Xia et al., 2026), we construct a specialized keyword corpus segmented into two distinct dimensions: Core RegTech, which captures terminology directly related to automated compliance, fraud management, and regulatory execution, and RegTech Enabling Technology, which assesses the underlying digital infrastructure such as artificial intelligence and big data implemented to support these regulatory functions. Operationally, we deploy Python-based crawling technology to automate the extraction and aggregation of these dimension-specific keywords from the banks' annual reports. To ensure cross-sectional comparability across the sample, the final RegTech adoption index is standardized by calculating the frequency of the identified keywords as a relative proportion of the total word count within each respective financial report as shown in table 1.

Table 1. Initial keywords of RegTech development index

Dimensions	Keywords
Core RegTech	"RegTech", "Regulatory technology", "Automated compliance", "Compliance automation", "Regulatory intelligence", "Compliance execution", "SupTech", "smart contract", "Anti-money laundering", "AML", "Know your customer", "KYC", "E-KYC", "Transaction monitoring", "Fraud management", "Identity management", "Fraud detection","Fraud Prevention", "Early warning signal", "EWS", "automated risk assessment", "Transactions Monitoring", "risk analytics", "transaction monitoring", "Data governance", "Regulatory reporting", "Risk data aggregation", "Real-time reporting", "IVR", "Voice Recognition", "Face recognition", "Fingerprint recognition", "Aadhaar authentication", "predictive analytics", "information security system", "Biometric"

RegTech Enablers	"Artificial intelligence", "ai", "machine learning", "ml", "big data", "chatbot", "bot", "robo-advisor", "data mining", "natural language processing", "nlp", "data analytics", "blockchain", "distributed ledger", "neural network", "Artificial neural network", "cloud compliance", "cybersecurity automation", "API integration", "Virtual Desktop Infrastructure", "VDI"

Source: *Compiled by author*

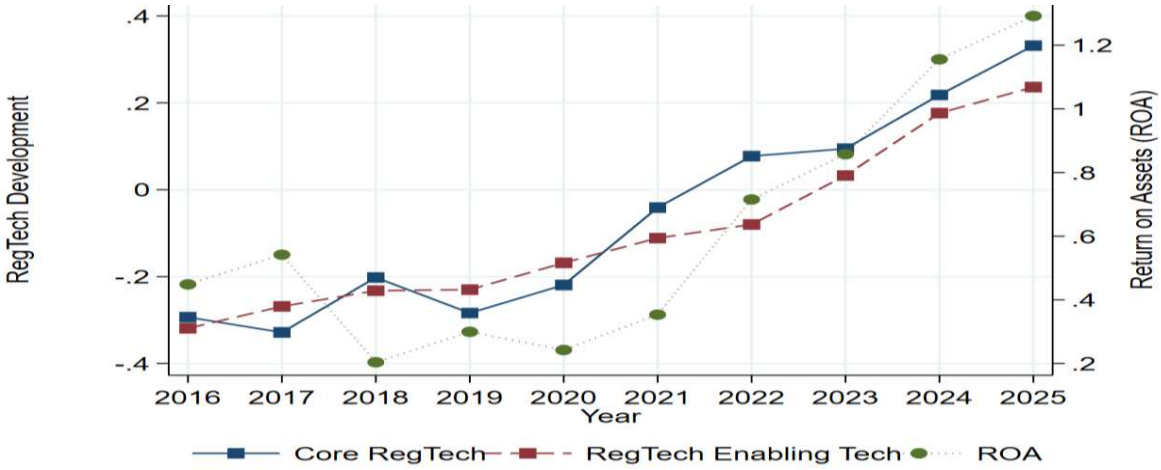
3.2.3 Control Variables

To rigorously isolate the specific impact of regulatory technology adoption on commercial bank profitability, this study incorporates a comprehensive set of both bank-specific and macroeconomic control variables that are empirically recognized to influence financial outcomes. At the institutional level, the models control for bank size (Size), measured by natural log of total assets, to account for potential economies of scale, alongside operational efficiency (CIR), which is calculated as the ratio of operating expenses to operating income. To capture the underlying risk profile and structural stability of the institutions, the analysis includes several critical indicators: solvency is measured by the Capital to Risk (Weighted) Assets Ratio (CRAR), liquidity risk is represented by the Loan-to-Deposit Ratio (LDR), and asset quality is evaluated using the ratio of net non-performing assets to net advances (NNPA). Furthermore, financial resilience is controlled for via the Provision Coverage Ratio (PCR), and the influence of corporate governance is integrated by accounting for board size (BS), defined as the total number of directors. Beyond internal institutional factors, the empirical framework adjusts for broader external economic conditions by incorporating country-level macroeconomic indicators, specifically annual GDP growth and the inflation rate (INF) derived from the World Bank's consumer price index. Finally, a COVID-19 dummy variable is introduced to mitigate the confounding effects of the pandemic-induced exogenous shock on the banking sector during the observation period. Institutional data for these control variables were systematically retrieved from the CMIE Prowess database to ensure analytical consistency across the sample.

3.2.4 Heterogeneity Variables

To conduct the subsample analysis detailed in Section 4.5, this study constructs two sets of categorical dummy variables based on institutional scale and ownership structure. First, to capture scale effects, banks are classified by size: the dummy variable "Large" takes a value of 1 if a bank's total assets exceed the sample median for a given year, and 0 otherwise. Conversely, "Small" takes a value of 1 if total assets fall below the sample median, and 0 otherwise. Second, to examine ownership dynamics, banks are categorized into "Public" and "Private" sectors. The "Public" dummy variable equals 1 if the institution is a state-owned or public sector bank, and 0 otherwise; similarly, the "Private" dummy equals 1 for private sector commercial banks, and 0 otherwise. The evolution of these RegTech adoption trends and overall bank profitability over the sample period is depicted in Fig. 2

Figure 2. Trends of RegTech adoption and bank profitability



Source: *Compiled by author*

A comprehensive summary of all main variable definitions and their corresponding data sources is provided in Table 2

Table 2. Main variable definitions

Variable Type	Variable Name	Character	definition	Data Source
Explained Variable	Return on Assets	ROA	Net profit to total assets	CIME Prowess
	Return on Equity	ROE	Net Income/Avg. shareholder' equity	
Core Explanatory Variable	Core Regulatory Technology	$RegTech_{CR}$	Keyword frequency of Core RegTech from annual reports	Annual reports
	RegTech Enabling Technology	$RegTech_{ET}$	Keyword frequency of RegTech enabling technology from annual reports	Annual reports
Control Variable	Bank Size	Log Size	Natural logarithm of Total assets	CIME Prowess
	Operational efficiency	CIR	Operating Expenses/Operating Income	CIME Prowess
	Solvency	Log CRAR	Natural logarithm of Tier 1 capital + Tier 2 capital/ Risk weighted assets	CIME Prowess
	Liquidity Risk	LDR	Total Loans/Total deposits	CIME Prowess
	Assets Quality	NNPA	Net nonperforming loans/Net advances	CIME Prowess
	Financial Resilience	PCR	Total provision/non-performing loans	CIME Prowess
	Board Size	Log BS	Natural logarithm of no. of directors	CIME Prowess
	Covid-19	Covid-19	Covid-19 dummy	
	GDP growth	GDP	Annual GDP growth	World Bank
	Inflation	INF	Consumer price index	World Bank

Source: *Compiled by author*

4. Empirical Results

4.1 Summary Statistics

Table 4 presents the descriptive statistics for the variables utilized in this study, comprising a total of 320 firm-year observations across the sample period. The primary dependent variable,

Return on Assets (ROA), exhibits a mean of 0.611 and a standard deviation of 0.954, with values ranging from a minimum of -1.61 to a maximum of 1.995, indicating significant variation in profitability across the sampled commercial banks. For the core explanatory variables derived from textual analysis, Core Regulatory Technology ($RegTech_{CR}$) shows a mean frequency of 0.064 with a standard deviation of 0.450, while RegTech Enabling Technology ($RegTech_{ET}$) records a mean of 0.096 and a standard deviation of 0.426. Among the bank-specific control variables, bank size (Natural logarithm of total assets) is 6.342, and the cost-to-income ratio (CIR), representing operational efficiency, averages 0.225 with a standard deviation of 0.093. The risk and stability metrics highlight an average Capital to Risk Assets Ratio (CRAR) of 2.734, a mean net non-performing assets (NNPA) ratio of 0.550, and a provision coverage ratio (PCR) averaging 0.730. Furthermore, corporate governance, proxied by natural logarithm of board size (BS), is 1.105. Finally, the macroeconomic control variables demonstrate an average annual GDP growth of 6.72% and a mean inflation rate (INF) of 4.72% over the observation window, while the Covid-19 dummy variable reflects a mean of 0.60, capturing the pandemic's temporal overlap with the dataset. Table 5 displays the correlation matrix for these variables.

4.2 Diagnostic tests and Model specification

To empirically analyze the influence of regulatory technology on the financial performance of commercial banks, this study establishes a panel data regression framework. Prior to finalizing the baseline model, a series of diagnostic tests were conducted to ensure statistical robustness shown in table 3. Multicollinearity is not a concern for this dataset, as the Variance Inflation Factor (VIF) of 1.83 is well below the standard problematic threshold. However, the Breusch–Pagan/Cook-Weisberg test ($\chi^2 = 18.18, p = 0.000$) and White test ($\chi^2 = 127.78, p = 0.004$) both strongly confirm the presence of heteroskedasticity, while the Wooldridge test (F = 3.640, p = 0.065) suggests marginal first-order autocorrelation. To determine the appropriate baseline estimator between Fixed Effects (FE) and Random Effects (RE), the Hausman specification test was employed. The test yielded a χ^2 statistic of 20.01 with a p-value of 0.066. Because this p-value exceeds the conventional 0.05 threshold, the null hypothesis that the unobserved individual-level effects are uncorrelated with the explanatory variables cannot be rejected at the 5% significance level.

Table 3. Diagnostic test results.

Test	Statistics	p-value
Panel Model Selection		
Hausman Test (FE vs RE)	$\chi2$ (12) = 20.01	0.066
Autocorrelation		
Wooldridge test	F (1, 31) = 3.640	0.065*
Heteroskedasticity		
Breusch–Pagan/Cook–Weisberg	$\chi2$ (1) = 18.18	0.000***
White test	$\chi2$ (1) = 127.78	0.004***
Multicollinearity (VIF)	1.83	

Source: *Compiled by author*

Table 4. Descriptive Statistics

Variable	Obs	Mean	S.D.	Min	Max
ROA	320	0.611	0.954	-1.61	1.995
$RegTech_{CR}$	320	0.064	0.450	0.616	0.987
$RegTech_{ET}$	320	0.096	0.426	0.443	1.075
Log Size	320	6.342	0.615	3.721	7.825
CIR	320	0.225	0.093	0.385	0.095
Log CRAR	320	2.734	0.238	2.016	3.516
LDR	320	0.224	0.455	0.204	1.190
NNPA	320	0.550	1.051	-2.525	2.814
PCR	320	0.730	0.140	0.400	0.980
Log BS	320	1.105	0.085	0.845	1.361
Covid-19	320	0.60	0.490	0.00	1.00
GDP	320	6.72	1.514	3.90	8.30
INF	320	4.72	1.328	2.40	6.70

Note: *Obs= number of observations, SD = standard deviation.*

Table 5. Correlation matrix

Variables	ROA	$RegTech_{CR}$	$RegTech_{ET}$	Log Size	CIR	Log CRAR	LDR	NNPA	PCR	BS	Covid-19	GDP	INF
ROA	1												
$RegTech_{CR}$	0.109	1											
$RegTech_{ET}$	0.245*	0.440*	1										
Log Size	0.024	0.217*	0.414*	1									
CIR	-0.652*	-0.063	-0.244*	-0.216*	1								
Log CRAR	0.602*	0.176*	0.187*	-0.083	-0.535*	1							
LDR	0.035	0.048	0.165*	0.308*	-0.134*	-0.112*	1						
NNPA	-0.764*	-0.234*	-0.237*	-0.009	0.562*	-0.562*	-0.158*	1					
PCR	0.129*	0.270*	0.171*	0.260*	-0.053	0.237*	0.028	-0.326*	1				
Log BS	-0.012	0.111*	0.220*	0.363*	-0.048	-0.058	0.015	0.008	0.018	1			
Covid-19	0.204*	0.386*	0.318*	0.196*	-0.140*	0.452*	-0.049	-0.282*	0.586*	-0.012	1		
GDP	0.163*	0.205*	0.108	0.034	-0.086	0.112*	0.000	-0.203*	0.127*	-0.081	0.186*	1	
INF	-0.085	-0.005	-0.042	0.011	-0.096	0.206*	-0.027	0.117*	0.099	-0.102	0.474*	-0.062	1

Note: **, **, and*** denote significance at the 10%, 5%, and 1% levels, respectively.*

Consequently, the Hausman test directs the selection of the Random Effects (RE) model as the most appropriate and efficient specification for this panel data. Accordingly, the baseline Random Effects regression model is specified as follows:

$$ROA_{it} = \beta_0 + \beta_1 RegTechCR_{it} + \beta_2 RegTechET_{it} + \beta_3 Size_{it} + \beta_4 CIR_{it} + \beta_5 CRAR_{it} + \beta_6 LDR_{it} + \beta_7 NNPA_{it} + \beta_8 PCR_{it} + \beta_9 BS_{it} + \beta_{10} Covid{-}19_{it} + \beta_{11} GDP_{it} + \beta_{12} INF_{it} + \mu_i + \epsilon_{it}$$

The empirical model utilizes a Random Effects panel data specification to mathematically define the relationship between regulatory technology adoption and the financial performance of commercial banks. In this equation, the dependent variable, ROA_{it} , represents the Return on Assets for a specific bank i at a given time t, capturing the institution's overall profitability. This performance metric is driven by a constant intercept, β_0, alongside a series of explanatory and control variables, where each respective β coefficient measures the magnitude and direction of that variable's impact on profitability. The primary independent variables of interest are $RegTechCR_{it}$ and $RegTechET_{it}$, which quantify the text-mined adoption frequencies of core regulatory technologies and foundational enabling technologies, respectively. To rigorously isolate these technological impacts, the equation systematically integrates several bank-specific control variables: institutional scale ($Size_{it}$), operational efficiency (CIR_{it}), capital adequacy ($CRAR_{it}$), liquidity risk (LDR_{it}), asset quality ($NNPA_{it}$), provision coverage (PCR_{it}), and corporate governance structure via board size (BS_{it}). Furthermore, the model adjusts for external macroeconomic conditions and exogenous shocks by including a COVID-19 dummy ($Covid - 19_{it}$), annual GDP growth (GDP_{it}), and the inflation rate (INF_{it}). Finally, consistent with a Random Effects framework, the model's composite error structure is bifurcated into μ_i, which accounts for the unobserved, time-invariant heterogeneity specific to individual banks, and ϵ_{it}, which represents the idiosyncratic error term capturing unobservable factors that vary across both banks and time.

4.3 Baseline regression

Table 6 presents the baseline regression results analyzing the impact of regulatory technology on the Return on Assets (ROA) of Indian commercial banks. The table displays eight distinct model specifications: columns (1) through (6) utilize Random Effects (RE) models with varying combinations of variables, column (7) applies Ordinary Least Squares (OLS), and column (8) employs a Fixed Effects (FE) estimator. Based on prior Hausman test diagnostics, the RE framework serves as the most appropriate baseline specification.

In the comprehensive RE model (Column 6) which incorporates both primary explanatory variables alongside all institutional and macroeconomic controls RegTech Enabling Technology ($\text{RegTech}_{\text{ET}}$) demonstrates a positive and statistically significant impact on bank profitability ($\beta = 0.202$, significant at the 5% level). This indicates that integrating foundational digital infrastructure, such as artificial intelligence and big data, actively enhances financial performance. Conversely, the coefficient for Core Regulatory Technology ($\text{RegTech}_{\text{CR}}$) is negative but statistically insignificant ($\beta = -0.133$). This suggests that investments strictly dedicated to automated compliance and regulatory reporting do not directly generate measurable profit gains for the banks.

Table 6. The results of baseline regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ROA	ROA	ROA	ROA	ROA	ROA	ROA	ROA
$RegTech_{CR}$	0.421***		0.153	-0.071		-0.133	-0.179**	-0.073
	(0.137)		(0.202)	(0.086)		(0.101)	(0.079)	(0.103)
$RegTech_{ET}$		0.598***	0.500**		0.159**	0.202**	0.146***	0.269**
		(0.150)	(0.217)		(0.079)	(0.098)	(0.068)	(0.126)
Size				0.066	0.024	0.027	0.042	0.453**
				(0.067)	(0.078)	(0.070)	(0.062)	(0.204)
CIR				-2.676***	-2.664***	-2.583***	-2.526***	-2.641***
				(0.566)	(0.587)	(0.547)	(0.460)	(0.754)
CRAR				0.714**	0.692**	0.700**	0.714***	0.700**
				(0.302)	(0.304)	(0.302)	(0.230)	(0.306)
LDR				-0.091	-0.079	-0.095	-0.161*	0.127
				(0.111)	(0.113)	(0.110)	(0.085)	(0.139)
NNPA				-0.493***	-0.488***	-0.492***	-0.500***	-0.500***
				(0.068)	(0.067)	(0.068)	(0.053)	(0.076)
PCR				-0.006	-0.005	-0.005	-0.007**	-0.006
				(0.005)	(0.005)	(0.005)	(0.003)	(0.006)
BS				-0.265	-0.357	-0.321	-0.311	-0.456
				(0.423)	(0.427)	(0.425)	(0.400)	(0.440)
Covid-19				0.075	-0.010	0.024	0.085	-0.154
				(0.175)	(0.174)	(0.180)	(0.090)	(0.210)
GDP				0.008	0.006	0.010	0.011	0.009
				(0.017)	(0.018)	(0.017)	(0.023)	(0.018)
INF				-0.067***	-0.051***	-0.056**	-0.065**	-0.024
				(0.020)	(0.019)	(0.020)	(0.027)	(0.021)
_cons	0.638***	0.668***	0.669***	-1.129	-0.895	-1.024	-1.185	-3.098*
	(0.115)	(0.108)	(0.108)	(1.088)	(1.129)	(1.097)	(0.823)	(1.718)
N	320	320	320	320	320	320	320	320
R^2	0.011	0.060	0.050	0.695	0.684	0.697	0.700	0.597
Prob > F	0.000	0.002	0.000	0.000	0.000	0.000	0.000	0.000

Note: *Standard errors are clustered at the firm level and are presented in parentheses; ∗, ∗∗, and ∗∗∗ denote significance at the 10%, 5%, and 1% levels, respectively. Model 1 to 6 are RE model with and without control and model 7 and 8 are OLS and FE.*

The baseline results also highlight the critical role of specific control variables in determining financial outcomes. Operational efficiency and asset quality are major drivers of profitability; the Cost-to-Income Ratio (CIR) and Net Non-Performing Assets (NNPA) exhibit highly significant negative coefficients ($\beta = -2.583$ and β = -0.492, respectively, both significant at the 1% level). This confirms that elevated operating expenses and deteriorating credit quality severely erode bank returns. Conversely, the Capital to Risk Assets Ratio (CRAR) shows a positive and significant relationship ($\beta = 0.700$, significant at the 5% level), emphasizing the performance advantages of maintaining robust capital adequacy. Among the external macroeconomic factors, inflation (INF) negatively impacts ROA (β = -0.056, significant at the 5% level). Other variables within this full RE specification including bank size, liquidity risk (LDR), provision coverage (PCR), board size (BS), GDP growth, and the COVID-19 dummy do not exhibit statistically significant effects on profitability. The alternative OLS and FE models in columns (7) and (8) broadly corroborate these core findings, reinforcing the positive influence of enabling technologies and the detrimental effects of operational inefficiency and non-performing assets

4.4 Endogeneity issue

To rigorously address potential endogeneity and capture the inherent persistence of financial performance, this study extends the empirical framework beyond static estimators to a dynamic

panel data specification utilizing the two-step System Generalized Method of Moments (System GMM). The dynamic panel regression model is specified as follows:

$$ROA_{it} = \alpha + \delta\, ROA_{i,t-1} + \beta_1\, RegTech_{CR_{it}} + \beta_2\, RegTech_{ET_{it}} + \sum_{k=1}^{K} Control_{k,it} + \mu_i + \epsilon_{it}$$

To ensure the robustness of our empirical findings, we executed preliminary diagnostics and adhered to strict methodological protocols. Given our panel structure (N > T), we implemented the System GMM estimator through three primary steps. First, we took measures to mitigate potential impact biases. Second, following Arellano and Bover (1995), we applied forward orthogonal deviations rather than the traditional first-difference transformation, as this approach maximizes sample retention within gapped panels. Third, to combat the risk of instrument proliferation identified by Roodman (2009), we restricted our internal instrument matrix by utilizing specific lag ranges and invoking the "collapse" suboption within the xtabond2 command. This constraint prevents the over-fitting of endogenous variables and bolsters the reliability of over-identification diagnostics. Finally, the model's structural integrity was verified using the Hansen test to confirm instrument exogeneity, alongside tests confirming the absence of serial correlation in the residuals.

Table 7. Two step system GMM results

	(1)	**(2)**	**(3)**
ROA_{t-1}	0.347***	0.275**	0.304***
	(0.112)	(0.102)	(0.073)
$RegTech_{CR}$	0.018		-0.089
	(0.750)		(0.115)
$RegTech_{ET}$		0.200*	0.323**
		(0.109)	(0.142)
Size	0.001	-0.046	-0.083
	(0.043)	(0.061)	(0.050)
CIR	-2.012***	-1.843***	-1.808***
	(0.459)	(0.528)	(0.375)
CRAR	0.249	0.323*	0.311*
	(0.192)	(0.175)	(0.169)
LDR	-0.196**	-0.194**	-0.169***
	(0.084)	(0.075)	(0.055)
NNPA	-0.358***	-0.385***	-0.354***
	(0.076)	(0.076)	(0.049)
PCR	-0.002	-0.003	-0.001
	(0.003)	(0.004)	(0.003)
BS	0.202	-0.070	-0.033
	(0.344)	(0.366)	(0.354)
Covid-19	0.057	-0.008	-0.002
	(0.105)	(0.114)	(0.107)
GDP	0.001	0.014	0.019
	(0.017)	(0.014)	(0.014)
INF	-0.028	-0.012	-0.006
	(0.022)	(0.018)	(0.018)
_cons	-0.910	-0.459	-0.359
	(0.725)	(0.975)	(0.940)
N	288	288	288
Bank FE	Yes	Yes	Yes
AR(1)	0.001	0.002	0.002
AR(2)	0.660	0.805	0.715

Hansen	0.341	0.612	0.671
No. of instruments	19	19	23
No. of groups	32	32	32

Notes: *Standard errors are reported in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels,*

Table 7 presents the empirical results of the dynamic panel data analysis utilizing the Generalized Method of Moments (GMM) estimator to address potential endogeneity and capture the persistence of financial performance. Across all three model specifications, the first-order lagged dependent variable (ROA_{t-1}) is positive and highly significant (ranging from $\beta = 0.275$ *to* $\beta = 0.347, p < 0.05$), which confirms that bank profitability is strongly persistent over time and justifies the use of a dynamic modeling approach.

In the comprehensive model (Column 3), which incorporates both technology dimensions, RegTech Enabling Technology (RegTech_{ET}) exhibits a strongly positive and statistically significant impact on bank profitability ($\beta = 0.323$, significant at the 5% level). This finding demonstrates that investments in foundational digital infrastructure yield a direct, measurable improvement in the return on assets. In contrast, the coefficient for Core Regulatory Technology (RegTech_{CR}) remains statistically insignificant ($\beta = -0.089$), reinforcing the premise that purely compliance-oriented technological adoptions do not serve as direct profit centers for commercial banks.

Regarding the control variables in the full specification (Column 3), asset quality and operational efficiency are reaffirmed as primary determinants of performance. The Cost-to-Income Ratio (CIR) and Net Non-Performing Assets (NNPA) both displays highly significant negative coefficients ($\beta = -1.808$ and $\beta = -0.354$, respectively, significant at the 1% level), indicating that high operational expenses and deteriorating credit portfolios severely constrain profitability. Additionally, liquidity risk, represented by the Loan-to-Deposit Ratio (LDR), negatively impacts returns (β = -0.169, significant at the 1% level), while capital adequacy (CRAR) provides a marginal positive performance premium ($\beta = 0.311$, significant at the 10% level). The remaining control variables Bank Size, Provision Coverage Ratio (PCR), Board Size (BS), COVID-19, GDP growth, and Inflation (INF) do not exert a statistically significant influence on ROA within this dynamic framework.

4.5 Heterogeneity analysis

Tables 8 and 9 present the empirical results of the heterogeneity analysis, which investigates whether the financial impact of technological adoption varies across institutional scale and ownership structure.

4.5.1 RegTech and bank performance classified by bank size

Table 8 presents the results of the heterogeneity analysis, estimating the dynamic panel model to determine whether the financial impact of technological adoption varies according to institutional scale. By interacting the technological dimensions with bank size classifications (Large and Small), the findings reveal significant asymmetrical effects across the Indian commercial banking sector. Consistent with the baseline dynamic estimations, the first-order

lagged dependent variable (ROA_{t-1}) remains positive and highly significant across all specifications, culminating in a strong persistence coefficient in the full model (Column 3, $\beta = 0.351, p < 0.01$).

Regarding the primary technological variables, the analysis isolates a profound divergence in how enabling technologies influence profitability based on bank size. In the comprehensive specification (Column 3), the interaction term for Enabling Technology among large institutions ($RegTech_{ET} \times Large$) demonstrates a powerful and highly significant positive impact on Return on Assets ($\beta = 0.525, p < 0.01$). Conversely, the interaction for small banks ($RegTech_{ET} \times Small$) is positive but fails to reach statistical significance (β = 0.129). This disparity strongly suggests that the financial benefits of foundational digital infrastructures such as artificial intelligence and big data are heavily concentrated among larger banks. These institutions likely possess the requisite economies of scale, extensive data repositories, and financial capital to fully actualize and monetize these technologies. A similarly stark contrast emerges regarding Core Regulatory Technology. For large banks, the interaction term ($RegTech_{CR} \times Large$) yields a statistically significant negative coefficient ($\beta = -0.734, p < 0.05$). For small banks, the interaction ($RegTech_{CR} \times Small$) is also negative but statistically insignificant ($\beta = -0.018$). This indicates that the substantial, ongoing capital expenditures required for large banks to deploy and maintain complex, automated compliance systems actively compress their overall asset returns, acting as a costly operational friction rather than a performance enhancer.

Finally, the control variables and diagnostic metrics in this subsample analysis align closely with previous models. Deteriorating asset quality ($NNPA, \beta = -0.336, p < 0.01$) and elevated liquidity risk ($LDR, \beta = -0.252, p < 0.01$) significantly depress returns. In contrast, robust capital adequacy ($CRAR, \beta = 0.284, p < 0.10$) and strong national economic growth ($GDP, \beta = 0.038, p < 0.05$) provide notable performance premiums.

Table 8. RegTech and bank performance according to bank size

	(1)	(2)	(3)
ROA_{t-1}	0.351***	0.194**	0.473***
	(0.095)	(0.089)	(0.096)
$RegTech_{CR} \times$ Large	0.082		-0.734**
	(0.221)		(0.302)
$RegTech_{CR} \times$ Small	-0.051		-0.018
	(0.088)		(0.058)
RegTechET × Large		0.298**	0.525***
		(0.135)	(0.252)
$RegTech_{ET} \times$ Small		0.158	0.129
		(0.129)	(0.083)
Large dummy	-0.004	-0.004	-0.005
	(0.079)	(0.081)	(0.078)
Size	-0.046	-0.048	-0.058
	(0.067)	(0.051)	(0.053)
CIR	-1.969***	-2.226***	-0.658
	(0.603)	(0.494)	(0.717)
CRAR	0.424**	0.312*	0.284*
	(0.206)	(0.166)	(0.159)
LDR	-0.123	-0.217***	-0.252***

	(0.084)	(0.075)	(0.066)
NNPA	-0.302***	-0.426***	-0.336***
	(0.076)	(0.068)	(0.063)
PCR	-0.002	-0.006*	-0.000
	(0.003)	(0.003)	(0.003)
BS	-0.030	0.062	0.010
	(0.345)	(0.344)	(0.313)
Covid-19	0.136	0.056	-0.052
	(0.099)	(0.104)	(0.094)
GDP	0.011	0.022	0.038**
	(0.017)	(0.014)	(0.014)
INF	-0.048**	-0.011	0.021
	(0.022)	(0.017)	(0.028)
_cons	-0.743	-0.535	-0.876
	(0.747)	(0.964)	(0.709)
N	288	288	288
Bank FE	Yes	Yes	Yes
AR(1)	0.002	0.003	0.003
AR(2)	0.740	0.965	0.547
Hansen	0.212	0.615	0.497
No. of instruments	24	24	28
No. of groups	32	32	32

Notes: *Standard errors are reported in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels,*

4.5.2 RegTech and bank performance classified by ownership

Table 9 extends the heterogeneity analysis by examining whether the financial impact of technological adoption differs between public and private sector banks. The empirical results reveal that private sector banks experience a statistically significant positive boost to their Return on Assets from integrating enabling technologies ($\beta = 0.253, p < 0.10$). In contrast, while the coefficient for public sector banks is also positive, it fails to achieve statistical significance ($\beta = 0.165$). This divergence suggests that private institutions may exhibit greater operational agility, allowing them to more effectively integrate and monetize foundational digital infrastructures. Furthermore, Core Regulatory Technology fails to demonstrate a statistically significant impact on profitability for either public or private banks. This seamlessly aligns with the baseline estimations, reinforcing the conclusion that automated compliance systems function primarily as mandatory operational safeguards rather than direct generators of profit, irrespective of a bank's ownership structure.

Table 9. RegTech and bank performance according to ownership

	(1)	**(2)**	**(3)**
ROA_{t-1}	0.249***	0.243***	0.225***
	(0.088)	(0.087)	(0.071)
$RegTech_{CR \times Public}$	0.060		0.071
	(0.087)		(0.092)
$RegTech_{CR \times Private}$	0.085		0.005
	(0.078)		(0.124)
$RegTech_{ET \times Public}$		0.270	0.165
		(0.207)	(0.148)
$RegTech_{ET \times Private}$		0.245**	0.253*
		(0.094)	(0.147)
Size	-0.047	-0.083	-0.101**
	(0.041)	(0.094)	(0.049)

CIR	-2.342***	-1.812***	-1.983***
	(0.348)	(0.475)	(0.251)
CRAR	0.481***	0.342**	0.466***
	(0.136)	(0.165)	(0.156)
LDR	-0.167**	-0.227***	-0.248***
	(0.063)	(0.062)	(0.049)
NNPA	-0.381***	-0.409***	-0.409***
	(0.068)	(0.065)	(0.060)
PCR	-0.006	-0.004	-0.005*
	(0.004)	(0.004)	(0.003)
BS	0.163	-0.192	0.088
	(0.261)	(0.432)	(0.231)
Covid-19	0.078	-0.005	0.003
	(0.111)	(0.101)	(0.089)
GDP	-0.001	0.017	0.003
	(0.015)	(0.014)	(0.011)
INF	-0.037**	-0.011	-0.017
	(0.016)	(0.018)	(0.014)
_cons	-0.813	-0.143	-0.574
	(0.640)	(0.884)	(0.789)
N	288	288	288
Bank FE	Yes	Yes	Yes
AR(1)	0.003	0.002	0.006
AR(2)	0.892	0.903	0.909
Hansen	0.578	0.686	0.836
No. of instruments	20	20	26
No. of groups	32	32	32

Notes: *Standard errors are reported in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels,*

4.6 Robustness Test

4.6.1 Bank RegTech and bank performance by eliminating largest and smallest bank

Table 10 presents the results of a robustness check conducted to ensure that the baseline empirical findings are not disproportionately driven by extreme institutional outliers. By re-estimating the dynamic System GMM model after removing the largest and smallest banks from the dataset, the total number of observations is appropriately reduced to 270. The results from this restricted sample strongly corroborate the primary estimations. In the fully specified model (Column 3), the coefficient for RegTech Enabling Technology (RegTech_{ET}) remains positive and statistically significant ($\beta = 0.397, p < 0.05$), reaffirming that foundational digital infrastructure actively enhances bank profitability even when size extremes are excluded from the analysis. Similarly, the coefficient for Core Regulatory Technology (RegTech_{CR}) remains statistically insignificant ($\beta = -0.102$), consistently demonstrating that strictly compliance-focused technologies do not directly generate measurable financial returns.

The structural persistence of profitability is also maintained, as the first-order lagged dependent variable (ROA_{t-1}) is positive and highly significant ($\beta = 0.400, p < 0.01$). Furthermore, the control variables behave consistently with the baseline dynamic model; operational inefficiency ($CIR, \beta = -1.671, p < 0.01$), deteriorating asset quality ($NNPA, \beta = -0.330, p < 0.01$), and liquidity risk ($LDR, \beta = -0.215, p < 0.05$) continue to exhibit significant negative impacts on the Return on Assets. Finally, the post-estimation diagnostics strictly validate the robustness of this modified sample.

Table 10. Removing Largest and Smallest Banks

	(1)	(2)	(3)
ROA_{t-1}	0.352***	0.240*	0.400***
	(0.114)	(0.132)	(0.121)
$RegTech_{CR}$	0.047		-0.102
	(0.075)		(0.102)
$RegTech_{ET}$		0.239*	0.397**
		(0.121)	(0.145)
Size	-0.028	-0.051	-0.095
	(0.046)	(0.076)	(0.065)
CIR	-2.470***	-1.960***	-1.671***
	(0.490)	(0.577)	(0.383)
CRAR	0.085	0.360	0.209
	(0.156)	(0.246)	(0.176)
LDR	-0.231**	-0.220**	-0.215**
	(0.099)	(0.093)	(0.080)
NNPA	-0.360***	-0.396***	-0.330***
	(0.074)	(0.084)	(0.070)
PCR	-0.003	-0.005	-0.002
	(0.004)	(0.005)	(0.004)
BS	0.225	-0.047	0.218
	(0.353)	(0.393)	(0.369)
Covid-19	0.062	0.017	0.029
	(0.096)	(0.131)	(0.108)
GDP	0.010	0.010	0.011
	(0.018)	(0.018)	(0.016)
INF	-0.020	-0.023	-0.003
	(0.026)	(0.028)	(0.029)
_cons	-0.518	-0.446	-0.380
	(0.544)	(1.112)	(0.798)
N	270	270	270
Bank FE	Yes	Yes	Yes
AR(1)	0.002	0.001	0.003
AR(2)	0.384	0.518	0.264
Hansen	0.577	0.759	0.276
No. of instruments	19	19	23
No. of groups	30	30	30

Notes: *Standard errors are reported in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels,*

4.6.2 Lag effect of bank RegTech on bank performance

Table 11 extends the dynamic panel analysis by incorporating the lagged effects of regulatory technology to evaluate its delayed impact on commercial bank profitability. Consistent with prior estimations, the first-order lagged dependent variable (ROA_{t-1}) remains positive and highly significant across all four model specifications, confirming the persistent nature of financial performance. The results demonstrate a sustained financial benefit from foundational digital infrastructure, as both the first and second lags of Enabling Technology ($RegTech_{ET_{t-1}}$ and $RegTech_{ET_{t-2}}$) yield positive and statistically significant coefficients ($\beta = 0.415, p < 0.01$ and $\beta = 0.244, p < 0.10$, respectively). This indicates that investments in technologies like AI and big data provide compounding, long-term enhancements to bank profitability. Conversely, Core Regulatory Technology exhibits a complex temporal effect. While its initial lag ($RegTech_{CRT_{t-1}}$) shows a statistically significant positive influence ($\beta = 0.181, p <$

0.01), the second lag ($RegTech_{CRT_{t-2}}$) turns negative and significant ($\beta = -0.240, p < 0.10$). This reversal suggests that while automated compliance may offer short-term operational efficiencies, the long-term, ongoing capital expenditures required to maintain these complex systems ultimately compress asset returns. Finally, key control variables such as operational inefficiency (CIR) and deteriorating asset quality (NNPA) consistently exert significant negative pressures on profitability across the models, and the post-estimation diagnostics including the Arellano-Bond and Hansen tests robustly validate the structural integrity of this lagged specification.

Table 11. Effect of one and two period lag of RegTech on bank performance

	(1)	**(2)**	**(3)**	**(4)**
ROA_{t-1}	0.364***	0.337***	0.404***	0.245***
	(0.110)	(0.113)	(0.108)	(0.083)
$RegTech_{CR\ t-1}$	0.181***			
	(0.054)			
$RegTech_{CR\ t-2}$		-0.240*		
		(0.135)		
RegTechET $_{t-1}$			0.415***	
			(0.144)	
RegTechET $_{t-2}$				0.244*
				(0.140)
Size	-0.058	-0.037	-0.097	-0.085
	(0.043)	(0.043)	(0.063)	(0.059)
CIR	-2.507***	-1.772***	-1.922***	-1.794***
	(0.481)	(0.528)	(0.475)	(0.447)
CRAR	0.206	0.250	0.336**	0.387**
	(0.191)	(0.157)	(0.162)	(0.179)
LDR	-0.193**	-0.160**	-0.228***	-0.215***
	(0.086)	(0.072)	(0.079)	(0.069)
NNPA	-0.314***	-0.424***	-0.306***	-0.432***
	(0.077)	(0.099)	(0.071)	(0.083)
PCR	-0.001	-0.001	0.002	-0.004
	(0.004)	(0.005)	(0.004)	(0.005)
BS	0.078	-0.028	0.053	-0.013
	(0.359)	(0.385)	(0.341)	(0.365)
Covid-19	-0.018	0.097	-0.177	-0.021
	(0.114)	(0.117)	(0.114)	(0.137)
GDP	0.010	0.004	0.016	0.018
	(0.018)	(0.016)	(0.020)	(0.016)
INF	-0.022	-0.014	0.010	-0.004
	(0.022)	(0.027)	(0.025)	(0.025)
_cons	-0.545	-0.511	-0.879	-0.463
	(0.711)	(0.781)	(0.850)	(0.861)
N	288	256	288	256
Bank FE	Yes	Yes	Yes	Yes
AR(1)	0.001	0.007	0.001	0.021
AR(2)	0.646	0.842	0.703	0.861
Hansen	0.751	0.296	0.694	0.398
No. of instruments	17	17	17	17
No. of groups	32	32	32	32

Notes: *Standard errors are reported in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels,*

4.6.3 Bank RegTech and bank performance by replacing dependent variable

Table 12 presents the results of an additional robustness check wherein the primary dependent variable, Return on Assets, is substituted with Return on Equity (ROE) to rigorously validate the empirical findings. Across all four dynamic model specifications, the first-order lagged dependent variable (ROE_{t-1}) remains positive and highly significant (ranging from $\beta = 0.298\ to\ \beta = 0.586$), strongly reaffirming the persistent nature of commercial bank profitability. The estimations perfectly corroborate the baseline results regarding the asymmetrical impact of technological adoption. Specifically, both the current level of Enabling Technology ($RegTech_{ET}$) and its first lag ($RegTech_{ET\,t-1}$) yield substantial and statistically significant positive coefficients ($\beta = 0.785, p < 0.05\ and\ \beta = 0.772, p < 0.05$, respectively). This demonstrates that foundational digital infrastructures, such as artificial intelligence and big data, robustly enhance shareholder value and overall financial performance. In contrast, Core Regulatory Technology whether analysed in its current period ($RegTech_{CR}$) or as a lag ($RegTech_{CRT\,t-1}$) fails to demonstrate any statistically significant impact on ROE. This consistently reinforces the conclusion that automated compliance systems function strictly as mandatory operational safeguards rather than direct profit centres.

Table 12. RegTech and bank performance by change dependent variable form ROA to ROE

	(1)	**(2)**	**(3)**	**(4)**
ROE_{t-1}	0.556***	0.298**	0.586***	0.535***
	(0.079)	(0.125)	(0.088)	(0.088)
$RegTech_{CR}$	0.043			
	(0.239)			
$RegTech_{CR\ t-1}$		-0.052		
		(0.321)		
$RegTech_{ET}$			0.785**	
			(0.381)	
$RegTech_{ET\ t-1}$				0.772**
				(0.305)
Control	Yes	Yes	Yes	Yes
N	288	288	288	288
Bank FE	Yes	Yes	Yes	Yes
AR(1)	0.000	0.001	0.000	0.000
AR(2)	0.351	0.547	0.285	0.397
Hansen	0.292	0.541	0.261	0.236
No. of instruments	19	19	19	19
No. of groups	32	32	32	32

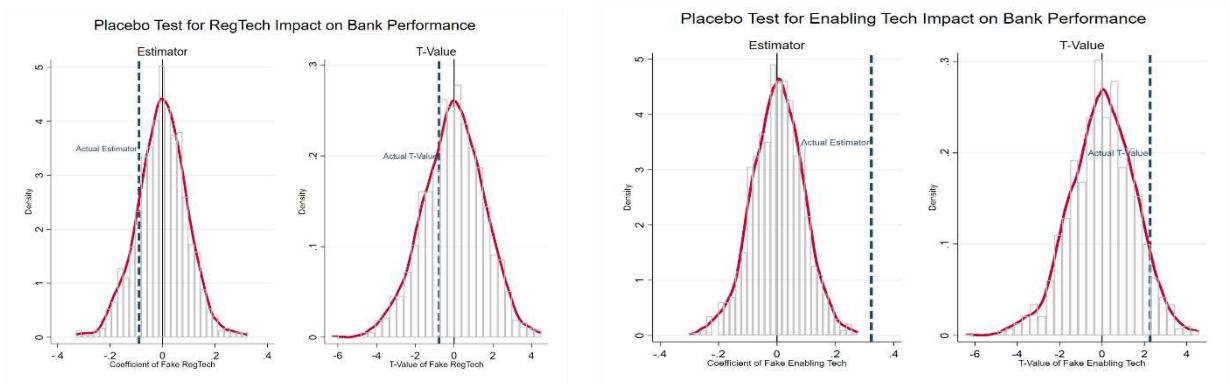
Notes: *Standard errors are reported in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels,*

4.6.4 Consider the omitted variable issue and the placebo test

To further validate the robustness of the baseline findings and ensure the results are not driven by unobserved spurious correlations or random data noise, this study conducts a placebo test utilizing a Monte Carlo simulation. Specifically, the text-mined technological adoption variables were randomly shuffled across the sample banks 1,000 times, and the baseline dynamic System GMM model was re-estimated for each iteration. The resulting distributions of the "fake" coefficients and t-values are plotted against the true baseline estimates.

For RegTech Enabling Technology, the actual baseline coefficient ($\beta = 0.323$) and its corresponding t-value sit strictly in the extreme right tail, falling entirely outside the normal bell curve of the 1,000 randomized estimates. This visually and statistically confirms that the positive impact of foundational digital infrastructure on bank profitability is genuine, highly unusual, and cannot be replicated by random chance. Conversely, the actual coefficient and t-value for Core Regulatory Technology fall squarely within the center of their respective randomized distributions. This perfectly aligns with the baseline estimations, reinforcing the conclusion that the non-significant financial impact of purely compliance-oriented technology is a consistent reality of the data structure rather than a statistical anomaly shown in figure 3.

Figure 3. Placebo test



5.0 Conclusion

Empirical evaluation of 32 Indian commercial banks from 2016 to 2025 reveals a complex, dual-mechanism relationship between RegTech integration and structural profitability. Utilizing a novel text-mining methodology to construct a bifurcated RegTech index. The results establish that foundational RegTech Enabling Technologies exert a statistically significant positive impact on performance by actively resolving information asymmetries and driving operational synergy. Conversely, Core Regulatory Technology fails to generate direct financial returns. Instead, these universally mandated systems function as structural cost frictions requiring heavy capital expenditure. Heterogeneity analyses further demonstrate that the financial premiums derived from enabling technologies are heavily concentrated among large and private-sector banks, while the massive compliance costs associated with core regulatory systems actively compress the asset returns of larger institutions.

From a theoretical standpoint, the findings advance the Resource-Based View (RBV) by mathematically distinguishing between synergistic digital resources and defensive compliance safeguards. Strategically, the evidence dictates that bank executives must deeply embed cross-functional enabling technologies to subsidize the heavy financial frictions imposed by mandatory compliance. For policymakers, the results highlight the urgent necessity to standardize compliance architectures, ensuring that high-frequency regulatory mandates do not disproportionately erode the intermediation efficiency of the banking sector.

6.0. Implications of the research

6.1 Managerial Implications

6.1.1 Cross-Functional Technological Embedding: Because Core Regulatory Technology imposes heavy structural frictions that compress asset returns, management must actively cross-subsidize these compliance costs. This is achieved by embedding RegTech Enabling Technologies (e.g., artificial intelligence and big data) deeply into core revenue-generating operations, such as credit underwriting and Treasury management.

6.1.2. Resolving Structural Inefficiencies: By leveraging these advanced foundational architectures, executives can directly resolve structural information asymmetries between the bank and borrowers. This strategic deployment allows institutions to drastically reduce their Cost-to-Income Ratio (CIR) and lower Net Non-Performing Assets (NNPA), ultimately driving the positive ROA and ROE metrics observed in the estimations.

6.1.3. Agility in Public Sector and Small Institutions: The heterogeneity results reveal that financial premiums are heavily concentrated in large and private-sector banks. Consequently, public-sector executives must dismantle bureaucratic bottlenecks to accelerate the deployment of predictive analytics and API integrations. Conversely, smaller banks lacking economies of scale should pivot toward collaborative technology models, such as shared cloud-compliance architectures, to mitigate severe fixed-cost burdens.

6.2 Policy Implications

6.2.1 Recognizing the "Profitability Paradox": Policymakers and central banking authorities like the Reserve Bank of India (RBI) must empirically recognize that mandating complex, automated transaction monitoring and real-time reporting (Core RegTech) forces banks into massive infrastructural trade-offs. This heavy, continuous capital expenditure temporarily erodes lending efficiency, particularly for large institutions overhauling massive legacy systems.

6.2.2. Standardizing Supervisory Architecture (SupTech): To mitigate sector-wide cost frictions, regulators should actively transition from simply issuing mandates to facilitating unified compliance ecosystems. Developing standardized, open-API regulatory reporting architectures would eliminate the redundant, disjointed IT capital expenditures currently borne by individual commercial banks.

6.2.3. Transitionary Support Mechanisms: To prevent high-frequency regulatory shifts from permanently depressing sector profitability, authorities should explore transitionary mechanisms for vulnerable institutions. Providing targeted technological subsidies or extended compliance implementation windows for public sector and smaller banks will ensure that the pursuit of absolute systemic transparency does not compromise broader credit-allocation capabilities.

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