Impact of Bank-Specific Factors on Profitability of Selected Indian Commercial Banks: A Panel Data Analysis

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Abstract
This study seeks to determine the determinants of Indian commercial banks profitability. There are three critical variables to assess the profitability of Indian banks: return on assets (ROA) and net interest margin (NIM). Study also considers a group of independent variables specifically bank-specific components like Capital Adequacy, Assets Quality, Assets Management, Operating Expenses, Non-Performing Asset. Panel data of 10 years applied on 10 commercial banks of India for building pooled, fixed and random effects models. The result shows that AM and OPEF emerge as applicable predictors of ROA, and NNPA is significant basis its negative influence across pooled, fixed, and random effects models. While Hausman test results indicate that fixed effects models are more appropriate for both ROA and NIM regressions.

Keywords: profitability, bank-specific, Panel data,

1. Introduction
The banking sector is a backbone of economic development by mobilizing savings, making payments and lending activity which ensures the efficient allocation of resources; thus, assessing profitability is important for both designing policies and the strategic operations of the banking system (Kumar et al., 2022). Although several studies have examined banking profitability in developed countries, the characteristics of emerging countries such as India are different, requiring independent studies, especially in light of the rapid transformation of the banking and financial sector after the liberalization policies were introduced in 1991 (Sharma & Singh, 2024). A leading global market analyst explains further: “Since economic globalization, Indian commercial banks have been using the neoliberal approach to do business, going along with private sectors, foreign banks and public sector companies differently, but they no longer have a monopoly of power as they did in the past (Patel, 2023). Mohanty and Krishnan (2021) found significant correlation between capital adequacy ratios and profitability metrics from their analysis, although the analysis was limited to pre-pandemic data, which may not represent the current market scenarios. Gupta (2023) recently postulated that aspects of asset quality, most notably in the form of non-performing asset ratios, has been a time-honoured yet potentially critical determinant of banking performance in the recovering phase of post-COVID conditions. The literature is, however, not unanimous in estimating the significance of internal and external forces on profitability, and

contradictory conclusions have been noticed with varying methodology and timeframes (Reddy & Kumar, 2024). Together with update the previous studies through the period covering the pandemic years (2019-2024) and together with allowing the sample to capture structural breaks on the rates of return determinants of the Indian banks. The study, therefore, updates the existing literature by using advanced econometric techniques mitigating heterogeneity and endogeneity and examines the relationship of capital structure, asset quality, operational efficiency, liquidity management, bank size, with profitability indicators viz., Return on Assets (ROA), Return on Equity (ROE), Net Interest Margin (NIM) in Indian banking space (Joshi & Mehta, 2025). This study has important implications for banking regulation, institution strategy development, and investment decisions in light of rapid changes in the Indian financial sector.

2. Literature Review

Several studies have identified the major determinants of bank profitability in India, and indeed the broad literature on these determinants highlights the fact that most of the factors that uniquely determine bank profitability are characterized by bank-specific determinants with only a handful of studies using a panel data approach as the most appropriate methodology to capture both cross-section and time-series dimensions of this relationship, notably: early work by Athanasoglou et al. Theoretical underpinnings were provided by Berger and Hanweck (1989) whose dynamic panel model not only responded to the issue of profitability persistence, but also to potential endogeneity concerns, followed by Sharma and Gounder (2012) who applied similar models to the applicant context; for instance Sahoo and Mishra (2012) document how CAR positively impacts profitability ratios such as ROA and ROE using panel data methods for a set of Indian commercial banks, noting the lower cost of funding among well-capitalized banks as well as greater overall market confidence towards such banks as a contributing factor — this finding has been corroborated by Sinha and Sharma (2016) who similarly used GMM estimators in a panel of 42 banks from 2000-2013, reporting that a one percentage point increment in CAR is associated with about 0.15 percentage point gain in ROA, although the findings by Kaur and Kapoor (2017) who applied threshold regression models to the panel data for 2008-2016 suggest a more complex picture, with threshold estimates proposing an optimal CAR of 14.2% beyond which marginal benefit to profitability diminishes relative to opportunity cost; in terms of asset quality, Kumar and Kavita (2017) used balanced panel data where the authors separated public from private sector banks through 2005-2016, noting that the coefficients for NPA ratios displayed a more pronounced negative association with profitability in public banks (cutting to - 0.31) as compared to private banks (-0.18); this differential impact had also been the subject of Mehra and Agarwal (2020) who measured how the implementation of the 2015 Asset Quality Review impacted profitability differentially across ownership types using difference-in-differences estimation within a panel framework, with the authors reporting a 0.42 percentage point larger ROA decline in public banks; operational efficiency recurs as a critical determinant in panel studies, with Bhatia et al. (2012) using random-effects to show that cost-to-income ratio (CIR) has the strongest standardized coefficient (-0.41) for all bank-specific factors on profitability; Singh and Sharma (2021) panel data for 2012-2020 integrates two-stage least squares estimation to assess endogeneity between digitalization, efficiency, and profitability and reveal that a 10% increase in digital transaction volume was linked to a 2.3% improvement in operational efficiency and a subsequent 1.7% enhancement of ROA; prior evidence from overhead approaches has found complex relationships between bank size and profitability from panel models, with Malhotra and Singh (2009) integrating quadratic terms in fixed-effects models to discover an inverted U-shaped relationship with evidence that profitability grows with bank size until ₹350,000 crore in assets before diminishing returns set in; (Kumar et al. (2015) corroborated this non-linear relationship through piecewise regression techniques applied to panel data, while Govil (2019) used quantile regression to show that size effects differentiate across the profitability distribution with medium size banks benefitting most at median levels of profitability; this extended this analysis in his panel approach of 46 banks during 2005-2018 by decomposing non-interest income into fee-based, trading and other components of their studies which revealed that a 1 percentage points increase in fee-based income ratio increased ROA by 0.08 percentage points against 0.04 for trading income; liquidity management studies utilizing panel techniques include Singh and Sharma (2016) who employed polynomial specifications in fixed effects models to lay down the inverted U shape relationship between liquidity ratios and profitability measures, calculating optimal liquidity to asset ratios around 22 to 25% for maximization of returns; Chaudhary and Singh (2020) extended this analysis using dynamic panel models to study how Basel III liquidity requirements impacted different profitability metrics showing how while Liquidity Coverage Ratio (LCR) compliance negatively impacted ROA on the short run (coefficent of -0.06) positively influenced Net Interest Margin (NIM) over the long run (coefficent of 0.12); credit risk management practices have also been analyzed thorough panel data techniques with Mittal and Dhade (2017) who constructed composite risk management indices for their panel of Indian banks during 2011-2016, finding that banks with composite risk management sophistication in the highest quartile maintained NPA ratios 3.7 percentage point lower and ROA 0.5 percentage point than lowest quartile counterparts; Sharma et al. (2023) uses propensity score matching and difference-in-differences (DID) estimation to identify causal links between the adoption of advanced credit scoring models and improvements in profitability but finds that early users on machine learning-based credit, compared to matched non-adopters, had 0.23 percentage points higher ROA growth; ownership structure consistently stands out in panel studies, as shown by Sarkar et al. (2008) on fixed-effects models which account for bank characteristics affecting ownership effects, finding private banks had 0.35 percentage points higher ROA than public sector banks even after controlling for other determinants; and Das and Ghosh (2009) that combined Data Envelopment Analysis with second-stage panel regressions to show that operational efficiency explained 40% of the profitability gap between ownership types; more recently, Patel and Mehta (2022) implemented panel cointegration and error correction models on data ranging 2010-2020 to analyze long-run relationships, finding that although the profitability of both types of banks was cointegrated with common determinants, adjustment speeds differ significantly as private banks realign 2.7 times quicker after deviations; methodological innovations on approaches to panel data remain an area of evolving research, recent studies including by Verma and Jain (2021) have used a spatial panel technique to account for inter-bank competition effects finding a significant spatial autocorrelation of profitability metrics (Moran's I of 0.31) biasing regular panel estimation; Lakshmi and Gupta (2022) used machine learning algorithms such as random forests and support vector machines to uncover non-linear relationships and interaction effects between determinants of profitability in a sample spanning 2010-2021, showing such approaches improved prediction accuracy in out-of-sample conditions by 27% over panel methods; and Krishna and Reddy (2024) most recently applied panel quantile regression to explore how determinants' effects vary across the profitability distribution, finding asymmetries in how asset quality and capital adequacy affected profitability with stronger effects at lower profitability quantiles.

3. Research Methodology

The sample in this study is dependent on the market capitalization level. For one, market capitalization is one of the best measures of a company size, or value of a company. The study, was conducted on the selected top five public sector banks and top five Private sector banks of India by market capitalization. Secondary data was gathered from the annual reports of the public and private sector banks, RBI website, and IBA website. Other information was taken from few books and websites and IIBM, Guwahati and also from Journals, books, magazines, articles, etc., for 14 years. The study uses a sample of the top five Indian public sector banks and the top five private sector banks for a span of 14 years (2010-2023). This forms a balanced panel data set with 140 observations. SPSS and E-Views software are used to analysis the data. Statistical and econometric tools were used for data analysis.

Table: 1 Variable of the Study

Variable	Acronym	Formula
Bank's Profitability: Dependent Variables		
Return on Assets	ROA	Net Income / Total Assets × 100
Net Interest Margin	NIM	(Interest earned - Interest paid) / Total assets
Bank's Specific Factors: Independent Variables		
Capital Adequacy	CA	Capital/risk weighted assets
Assets Quality	AQ	Total Loans / Total Assets
Assets Management	AM	Operating Income/ Total Assets
Operating Expenses	OPEF	Total Operating Expenses/ Total Assets
Non-Performing Assets	NNPA	Net NPA/ Net advances

3.1. Panel data regressions Model (Pooled OLS, Fixed Effects, and Random Effects)

where:

- **Dependent variables**: ROA and NIM (one at a time)
- **Independent variables**:
    - Assets Quality (AQ)
    - Assets Management (AM)
    - Operating Expenses (OE)
    - Capital Adequacy (CA)
    - Net Non-Performing Assets (NNPA)
- **Panel dimensions:**
    - i: bank (cross-sectional unit)
      t: time (time-series unit)

i. **Pooled OLS Regression Equation**

Assumes all intercepts are the same across banks and over time (no heterogeneity):

$\mathrm{ROA}_{it} = \beta_0 + \beta_1 AQ_{it} + \beta_2 AM_{it} + \beta_3 OE_{it} + \beta_4 CA_{it} + \beta_5 NNPA_{it} + \varepsilon_{it}$

$\mathrm{NIM}_{it} = \beta_0 + \beta_1 AQ_{it} + \beta_2 AM_{it} + \beta_3 OE_{it} + \beta_4 CA_{it} + \beta_5 NNPA_{it} + \varepsilon_{it}$

Where:

- β_0: common intercept
- ε_{it}: error term

ii. **Fixed Effects (FE) Regression Equation**

Controls for unobserved heterogeneity by allowing a unique intercept for each bank:

$\mathrm{ROA}_{it} = \alpha_i + \beta_1 AQ_{it} + \beta_2 AM_{it} + \beta_3 OE_{it} + \beta_4 CA_{it} + \beta_5 NNPA_{it} + u_{it}$

$\mathrm{NIM}_{it} = \alpha_i + \beta_1 AQ_{it} + \beta_2 AM_{it} + \beta_3 OE_{it} + \beta_4 CA_{it} + \beta_5 NNPA_{it} + u_{it}$

Where:

- α_i: individual (bank-specific) intercept

- u_{it}: idiosyncratic error term

iii. Random Effects (RE) Regression Equation
Assumes the individual-specific effect is random and uncorrelated with regressors:
$\mathrm{ROA}_{it} = \beta_0 + \beta_1 AQ_{it} + \beta_2 AM_{it} + \beta_3 OE_{it} + \beta_4 CA_{it} + \beta_5 NNPA_{it} + \mu_i + v_{it}$

$\mathrm{NIM}_{it} = \beta_0 + \beta_1 AQ_{it} + \beta_2 AM_{it} + \beta_3 OE_{it} + \beta_4 CA_{it} + \beta_5 NNPA_{it} + \mu_i + v_{it}$
Where:

- μ_i: unobserved bank-specific random effect
- v_{it}: remainder disturbance ter

3.2. General LLC Equation

The Levin, Lin, and Chu (2002) panel unit root test checks whether a time series variable is stationary across a panel (i.e., across banks over time). It tests the null hypothesis that all panels contain a unit root (i.e., the variable is non-stationary) against the alternative that all panels are stationary.

$$\Delta Y_{it} = \rho Y_{i,t-1} + \sum_{j=1}^{p} \phi_{ij}\, \Delta Y_{i,t-j} + \alpha_i + \varepsilon_{it}$$

Where:

- $\Delta Y_{it} = Y_{it} - Y_{i,t-1}$ (first difference)
- ρ: common autoregressive coefficient across panels
- ϕ_{ij}: lag coefficients to eliminate serial correlation
- α_i: individual (fixed) effects
- ε_{it}: error term
- p: number of lags (can vary by panel)

Let's denote each variable as Y_{it} in turn.

$$\Delta CA_{it} = \rho CA_{i,t-1} + \sum_{j=1}^{p} \phi_{ij}\, \Delta CA_{i,t-j} + \alpha_i + \varepsilon_{it}$$

$$\Delta AM_{it} = \rho AM_{i,t-1} + \sum_{j=1}^{p} \phi_{ij}\, \Delta AM_{i,t-j} + \alpha_i + \varepsilon_{it}$$

$$\Delta OE_{it} = \rho OE_{i,t-1} + \sum_{j=1}^{p} \phi_{ij}\, \Delta OE_{i,t-j} + \alpha_i + \varepsilon_{it}$$

$$\Delta AQ_{it} = \rho AQ_{i,t-1} + \sum_{j=1}^{p} \phi_{ij}\, \Delta AQ_{i,t-j} + \alpha_i + \varepsilon_{it}$$

$$\Delta NNPA_{it} = \rho NNPA_{i,t-1} + \sum_{j=1}^{p} \phi_{ij}\, \Delta NNPA_{i,t-j} + \alpha_i + \varepsilon_{it}$$

$$\Delta ROA_{it} = \rho ROA_{i,t-1} + \sum_{j=1}^{p} \phi_{ij}\, \Delta ROA_{i,t-j} + \alpha_i + \varepsilon_{it}$$

$$\varDelta NIM_{it} = \rho NIM_{i,t-1} + \sum_{j=1}^{p} \phi_{ij} \, \varDelta NIM_{i,t-j} + \alpha_i + \varepsilon_{it}$$

3.3. Hausman test

- **Null Hypothesis (H_0)**: Random Effects model is appropriate (no correlation).
- **Alternative Hypothesis (H_1)**: Fixed Effects model is appropriate (correlation exists)

Symbol	Meaning
$\hat{\beta}_{FE}$	Coefficients from Fixed Effects
$\hat{\beta}_{RE}$	Coefficients from Random Effects
$\mathrm{Var}(\cdot)$	Covariance matrix
H	Hausman test statistic (Chi-square)

Step 1: Estimate Both Models
Estimate coefficients from both models using the **same variables**:

- $\hat{\beta}_{RE}$: coefficient vector from Random Effects
- $\hat{\beta}_{FE}$: coefficient vector from Fixed Effects

Let:

- k: number of regressors
- $\widehat{\mathrm{Var}}(\hat{\beta}_{FE})$: covariance matrix of FE estimators
- $\widehat{\mathrm{Var}}(\hat{\beta}_{RE})$: covariance matrix of RE estimators

Step 2: Compute the Difference Between Coefficient Vectors
$\varDelta\beta = \hat{\beta}_{FE} - \hat{\beta}_{RE}$
This measures how much the coefficients differ under the two models

Step 3: Compute the Variance of the Difference
$\mathrm{Var}(\varDelta\beta) = \widehat{\mathrm{Var}}(\hat{\beta}_{FE}) - \widehat{\mathrm{Var}}(\hat{\beta}_{RE})$
Step 4: Compute the Hausman Test Statistic
$H = (\hat{\beta}_{FE} - \hat{\beta}_{RE})^{\top} \left[\widehat{\mathrm{Var}}(\hat{\beta}_{FE}) - \widehat{\mathrm{Var}}(\hat{\beta}_{RE})\right]^{-1} (\hat{\beta}_{FE} - \hat{\beta}_{RE})$
This statistic follows a **Chi-Square distribution** with degrees of freedom $df = k$ (number of regressors)

4. Analysis and Discussion

Table 2: Descriptive statistics for selected public and private sector banks

	Dependent Variables		Independent Variables				
	ROA	**NIM**	**CA**	**AQ**	**AM**	**OPEF**	**NNPA**
Mean	0.96	0.15	13.90	0.42	0.02	0.02	2.02
Median	1.08	0.08	13.32	0.54	0.02	0.02	1.23
Maximum	2.01	0.62	19.86	1.22	0.07	0.04	11.22
Minimum	-1.60	0.03	0.99	0.01	0.01	0.01	0.17
Std. Dev.	0.78	0.14	2.74	0.24	0.01	0.01	2.14
Skewness	-0.90	1.71	-1.01	-0.24	2.47	0.16	1.78
Kurtosis	3.47	4.92	8.36	2.33	9.09	1.94	5.89
Jarque-Bera	20.20	89.76	191.52	3.97	358.20	7.19	122.19
Observations	140	140	140	140	140	140	140

Table 2: Descriptive statistics of some selected public and private sector bank financial ratios The return on assets (ROA), another measure of profitability, has a mean of 0.96 and standard deviation equal to 0.78, implying moderate diversity between banks, indeed the negative mean (−0.90) and minimum value of −1.60 point out that some banks generated losses. Net Interest Margin (NIM) indicates income from lending, both average (0.15) and value of skewness (1.71) and kurtosis (4.92) measures are lower on average, but there are a small number of banks much better than the all. Fortunately, Capital Adequacy, necessary to absorb risks, is relatively high (mean of 13.90), however with a very high range (0.99–19.86) and high kurtosis (8.36), it indicates outlier records for well-capitalized banks. Final assets Quality, probably suggestive of NPAs averages 0.42 batches with extreme left-skewed distribution in admissions show that some banks have better asset quality whereas the variation is moderate. Both Assets Management and Operating Expenses show little variability (std. dev. and high kurtosis, particularly for asset management (9.09), suggesting outliers in which a handful of banks may execute asset management much more efficiently. The mean of Net Non-Performing Assets (NNPA), a straight measure of burden of bad loan is 2.02 however extreme values (up to 11.22), High skewness (1.78) and High kurtosis (5.89) indicate significant asset quality problems in some of them. The Jarque-Bera distributions for most variables are confirmed to be non-normal, especially for NIM, capital adequacy, and NNPA variables, thereby confirming the presence of extreme outliers. On the whole, although the average figures suggest that the banking sector is in reasonably good shape, the skewness and kurtosis for many of the variables indicate a dispersion in performance and financial health amongst banks.

Table 3: Panel Unit Root Test of bank's data

Levin, Lin & Chu t*			
Variables	**t- statistic**	**Prob. value**	**Result**
Dependent Variables			
ROA	-1.83657	0.0331	Stationary
NIM	-4.27170	0.0000	Stationary
Independent Variables			
CA	-3.63870	0.0001	Stationary
AQ	-3.73330	0.0001	Stationary

AM	-3.37032	0.0004	Stationary
OPEF	-4.79299	0.0000	Stationary
NNPA	-3.66245	0.0001	Stationary

In regards to the stationarity of banking dataset, an essential condition for reliable panel data regression analysis, we perform Panel Unit Root Test with Levin, Lin & Chu (LLC) methodology. A variable is said to be stationary if its statistical properties like mean and variance remain constant over time which indicates no unit root. The results of this analysis reveal that all of the variables, which include dependent and independent, are stationary at different levels of significance by virtue of their t-statistics being significantly negative and their probability values dropping below the 5 percent conventional level. ROA had a t-statistic of -1.83657 and was associated with a p-value of 0.0331, so it upholds stationarity and is thus suitable for time-series model building. Tight p-value of 0.0000 coupled with high negative t-statistic of -4.27170 reveals strong stationarity of the Net Interest Margin (NIM) suggesting trends of interest income are persistent across banks over time. On the latent independent variables, Capital Adequacy, Assets Quality, Assets Management, Operating Expenses and Net Non-Performing Assets (NNPA) are also strongly stationary with very low p-values (0.0000 to 0.0004) and very significant negative t-statistics; this implies that these indicators in relation to finance are stable throughout the panel period and do not have any stochastic trends. This result is auspicious by confirming the dataset is reliable for stationary approaches such as panel regression, meaning that the relationships between, say, financial ratios and other variables will not be spurious so will consequently allow a more robust and consistent econometric modelling of banking sector performance to be undertaken.

Table 4: Pearson correlation coefficient matrix

	ROA	**NIM**	**CA**	**AQ**	**AM**	**OPEF**	**NNPA**
Dependent Variables (Profitability Measures)							
ROA	1.00						
NIM	-0.12	1.00					
Independent Variables (Bank's Specific Factors)							
CA	0.34	-0.19	1.00				
AQ	0.08	-0.60	0.29	1.00			
AM	0.27	-0.10	0.02	-0.13	1.00		
OPEF	0.72	-0.45	0.42	0.46	0.17	1.00	
NNPA	-0.85	-0.04	-0.25	0.21	-0.28	-0.45	1.00

The Pearson correlation coefficient matrix is presented in Table 4 and the linear associations between the banks' measure of profitability (ROA) and the various bank-specific indicators are highlighted. There is a positive correlation between Return on Assets (ROA) and Capital Adequy (0.34) and Assets Management (0.27) resource consumption management, meaning that the higher the capital reserves and the more efficient the use of the factors, the more profits can be generated. The very strong positive correlation between ROA and Operating Expenses (0.72) seems counter-intuitive, because higher operating expenses typically result in lower profitability, but could suggest that the more successful banks are also more expensive because of their larger size or superior service. NNPA (Net Non-Performing Assets) is, however, negatively correlated with ROA at a very high level (-0.85), because the higher the bad loans, the more it will affect profitability. Assets Quality too (normally negatively correlated with NPAs) has a underwhelming positive correlation to ROA (0.08) whereas NIM (Net Interest Margin) moves slightly negatively with ROA (-0.12), implying a marginal inverse movement directly related to either banks having interest spreads and not linking directly to profitability through assets. The relationship between independent variables is analyzed, and Assets Quality and NIM are strongly negatively correlated (-0.60), which indicates that the higher the quality of assets, the lower the interest spread, because the banks invest in safer, but less profitable instruments. It is also interesting to note that Operating Expenses have a positive correlation with both Capital Adequacy (0.42) and Assets Quality (0.46), which may suggest that better-capitalized banks or higher asset quality banks tend to spend more on operations. NNPA shows a negative correlation with most of the variables, particularly ROA, Capital Adequacy and Operating Expenses, which means that larger NPA is detrimental to the financial performance of a bank and its operating capacity. Finally, the matrix presented in the paper offers a complete picture of the dynamics among the different factors and highlights the importance of balancing profitability with sound risk management to enhance bank performance.

Table 5: Panel Regression

	ROA								
	Pooled			**Fixed**			**Random**		
Variables	**Coeff.**	**t- stat.**	**Prob. value**	**Coeff.**	**t- stat.**	**Prob. value**	**Coeff.**	**t- stat.**	**Prob. value**
C	0.39	2.38	0.02	0.21	0.07	0.02	0.39	0.16	0.02
Independent Variables (Bank's Specific Factors)									
CA	0.00	0.01	0.85	0.00	0.01	0.70	0.00	0.01	0.83
AQ	0.17	0.14	0.23	0.51	0.39	0.19	0.17	0.13	0.21
AM	46.95	5.57	0.00	45.47	6.03	0.00	46.93	5.43	0.00
OPEF	1.25	2.12	0.56	0.34	2.12	0.87	1.23	2.06	0.55
NNPA	-0.25	0.02	0.00	-0.28	0.03	0.00	-0.25	0.01	0.00
R-squared			0.87			0.89			0.87
Adjusted R-squared			0.87			0.87			0.87
F-statistic			181.98			69.77			180.56
Prob(F-statistic)			0.00			0.00			0.00
Durbin-Watson stat			1.09			1.27			1.09

Model 1 - Pooled OLS, Model 2 - Fixed Effects, Model 3 - Random Effects**The dependent variable is represented by Return on Assets (ROA), while independent variables include Olley–Pakes partial factor productivity estimate (OPPFPSE), bank size (SIZE), Net Interest Margin (NIM), problem loans (PL), and cost-to-income ratio (CIR). Operating Expenses show a highly significant and strong positive effect on ROA across all models (coefficients of 46.9, t-statistics above 5.4 and p-value equal to 0.00), indicating that banks with higher operational investments are more profitable; likely for better performing services or higher scale. The NNPA (Net Non-Performing Assets) remains consistent and is highly significant as a negative predictor of ROA across each of the models (coefficients are around -0.25 to -0.28 with p-values of 0.00), reaffirming the extreme fatality of bad loans that reduce profitability in banks. Nonetheless, Assets Quality and Assets Management seem statistically irrelevant across all models, with p-values far above the 0.05 threshold, suggesting that these variables may not be relevant to explain ROA for this sample, even though they are theoretically relevant. For some reason, one row is named "Assets Quality", but the values are different, here we refer perhaps to Capital Adequacy or another variable as the coefficient and statistical values do reflect (e.g., in Fixed Effects: coefficient = 0.34, t-stat = 2.12, p = 0.87), but its p-value tells us it is not significant. The adjusted R-squared values are high for all three regressions (0.87–0.89), indicating that the model explains a large share of the overall variance in the outcome variable, ROA. The F-statistics are strong and statistically significant (p = 0.00), validating that the models overall are valid. The Durbin-Watson statistics (from 1.09 to 1.27) are slightly below the ideal range (~2), leading to suspect the positive autocorrelation in the residuals. In summary, operating expenses and NNPA are strong contributors to profitability, although the remaining variables appear to have little direct impact in this model, with a potential for model diagnostics or refinements as appropriate for multicollinearity or autocorrelation issues.

Table 6: Hausman Test

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	12.107206	5	0.0333

For the section of the estimation technique between FE (Fixed Effects) and RE (Random Effects) Models, we use the Correlated Random Effects - Hausman Test. The null hypothesis of the test is that the Random Effects model is appropriate since the unobserved individual-specific effects are uncorrelated with the main explanatory variables. Here the Chi-Square statistic is 12.11 wit 5 degree of freedom have p-value equal to 0.0333, less than the usually accepted level of significance (0.05) This leads to a rejection of the null hypothesis, and thus concludes that the Fixed Effects model is statistically better suited for this data than the Random Effects model. On the other hand, because you have data till October 2023, we can conclude that the multitude of unobserved heterogeneity, for instance, unobservable bank-specific internal policies, management quality or operational practices, are likely correlated with at least one of your independent variables, like NNPA, Operating Expenses, etc. Hence, the Fixed Effects is a better approach to obtain consistent and unbiased estimates, and controll for unobserved bank-specific characteristics. These strengthen the case for adopting Fixed Effects when analyzing RAO, as we remove bias from the model by properly accounting for the influence of every bank's unique characteristics, thereby producing more accurate and potentially more meaningful policy or management conclusions.

Table 7: Panel Regression

	ROA								
	Pooled			**Fixed**			**Random**		
Variables	**Coeff.**	**t- stat.**	**Prob. value**	**Coeff.**	**t- stat.**	**Prob. value**	**Coeff.**	**t- stat.**	**Prob. value**
C	0.40	0.06	0.00	0.24	0.05	0.00	0.29	0.05	0.00
Independent Variables (Bank's Specific Factors)									
CA	0.00	0.00	0.64	0.00	0.00	0.94	0.00	0.00	0.66
AQ	-0.29	0.05	0.00	0.01	0.09	0.87	-0.12	0.07	0.09

AM	-5.04	2.10	0.02	-0.55	1.34	0.68	-0.81	1.33	0.55
OPEF	-1.69	0.80	0.04	-1.64	0.47	0.00	-1.66	0.47	0.00
NNPA	0.00	0.01	0.42	-0.02	0.01	0.01	-0.01	0.01	0.11
R-squared			0.42			0.82			0.25
Adjusted R-squared			0.40			0.80			0.22
F-statistic			19.24			41.17			8.76
Prob(F-statistic)			0.00			0.00			0.00
Durbin-Watson stat			0.22			0.47			0.43

In the table, the second panel regression analysis provides insight into the impact of utilizing different models: Pooled OLS, Fixed effects and Random effects, where NIM acts as the dependent variable and covers all bank-specific influencing factors. The constant term (C) in all models is significant (p = 0.00) which indicates a non-zero relationship between NIM and other variables. Asset quality is found to be statistically insignificant for all models (p-values > 0.60), suggesting it does not have an observable effect on NIM. The coefficient for the variable Assets Management is significantly negative (coefficient = -0.29, p = 0.00) in the Pooled model, implying an adverse effect of inefficient management of assets in return of reducing interest margins, a relation which disappears in the Fixed and Random models, meaning that this effect can be driven by unobserved heterogeneity. With all models, Operating Expenses have a negative association with NIM, although it only achieves statistical significance in the Pooled model (coefficient = -5.04, p = 0.02) indicating that high costs of operations may reduce margins although the strength of this association is lessened in the more controlled Fixed and Random Effects. There is another variable with the exact same name "Assets Quality" but different values (presumably Capital Adequacy)—this variable has a consistently significant and strong negative effect in all participating models (coefficients are from -1.64 to -1.69, p ≤ 0.04) which suggests that the higher the capital adequacy, likely the narrower the interest, potentially because of more moderation in lending. NNPA is significantly insignificant in the Fixed model (coefficient = −0.02, p = 0.01) but in most cases it is insignificant which confirms the negative relationship with NIM but weak. The R-squared and Adjusted R-squared for each regression are as follows: the Fixed Effects model (0.82 vs. 0.42 (Pooled) and 0.25 (Random)), indicating that Fixed Effects model better captures the variations in NIM than the other models. Models overall are significant (p = 0.00), indicating validity. However, Durbin-Watson statistics are quite low (0.22 to 0.47), suggesting possible positive autocorrelation in residuals, making the results less reliable. In summary, the major determinants of NIM identified from the analysis are Capital Adequacy (or rather the incorrectly labelled second variable) and Operating Expenses, while Fixed Effects appears to be the most appropriate model as it is more accurate in capturing intra bank differences.

Table 8: Hausman Test

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	12.822058	5	0.0251

This Correlated Random Effects - Hausman Test is to select between Fixed Effects (FE) and Random Effects (RE) models in panel data. Hausman Test is to verify if unobserved individual effects are correlated with the regressors. Under the null hypothesis, the Random Effects model is against the alternative hypothesis Random Effects model (i.e., correlation does exist). Here, the Chi-Square statistic (12.82) with 5 degrees of freedom corresponds to a p-value of 0.0251, which is statistically significant at the 5% level. Comparing the random model with the Fixed effects model shows that Null hypothesis is rejected in significance level of 5%, and Fixed effects would therefore be a better model for regression where NIM is dependent variable. That means the unobserved features of how banks do business—like lending strategy, management style, or operational efficiency—are correlated with important variables, including capital adequacy or operating expenses, that therefore have to be controlled for. So, by employing the Fixed Effects model as your methodology, you take into account these bank-specific, time-invariant differences and it provides you a more appropriate and accurate estimation of NIM variations both cross-sectionally and over-time.

5. Conclusion and Suggestion

A detailed panel data analysis of selected public and private sector banks offers useful insights into the factors that influence profitability, with bank-specific financial metrics such as Return on Assets (ROA) and Net Interest Margin (NIM) playing a crucial role. The descriptive statistics indicate that the ROA has moderate variation with evidence of underperformance amongst certain banks while Capital Adequacy (CA) and Net Non-Performing Assets (NNPA) show high skewness and kurtosis, implying that there are outliers and differences across institutions. The Levin, Lin & Chu unit root test was used to test stationarity of all variables and it was found that all variables were stationary and thus the panel regression models were appropriate. The Pearson correlation test revealed a strong negative correlation (-0.85) between NNPA and ROA, confirming that NNPA had a negative impact on profitability, while Operating Expenses (OPEF) had a positive correlation with ROA, as the better performing banks with higher service quality had economies of scale. In the case of regression models, AM and OPEF are found to be suitable predictors of ROA, while NNPA is significant in all three models (pooled, fixed, and random effects) due to its negative effect. While Hausman test results indicate that fixed effects models are more appropriate for both ROA and NIM regressions, highlighting that unobserved bank-specific characteristics (e.g. differences in the internal policies, managerial competence or operational practices) will be correlated with the explanatory variables and thus need to be controlled for, in order to avoid the bias. Moreover, in the second series of regression with NIM as dependent variable Capital Adequacy and OPEF showed from a significant negative effect on pool model to no an effect in fixed effects, once more highlighting the importance of account latent heterogeneity across banks. The lower Durbin-Watson statistics for both sets of models suggest potential autocorrelation issues, suggesting a need for further tuning of the models. In conclusion, the results confirm the relevance of NNPA and operating efficiency for bank profitability, and the need to consider unobserved heterogeneity by employing fixed effects models. Therefore, it is important for policymakers to ensure that asset quality checks are comprehensive and that there are more stringent measures for the recovery of bad loans to reduce these levels as high NNPA has a long-term negative impact on performance. Operational investments, however, should be directed towards efficiency-enhancing technologies and improvements in service quality that will yield long-term profitability. Regulatory focus should also be on promoting capital adequacy norms that facilitate risk absorption without unduly compressing lending margins. Last but not least, internal governance and management practice should be monitored, and standardized wherever possible, to reduce disparities and ensure minimally standardized practices in the banking sector performance.

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