Advances in Consumer Research
https://acr-journal.com/
Volume-3 | Issue-11|July: 2026
Original Researcher Article

What Drives Bank Profitability in India? A Dynamic Two-Way Fixed-Effects Analysis of Selected Public and Private Sector Banks (2005–2025)

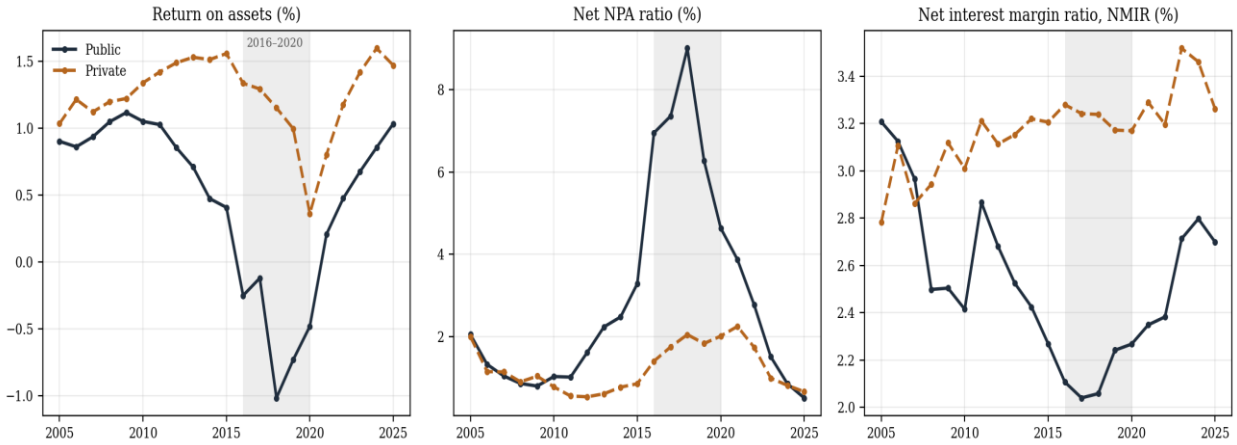
Dr. R Sushma[1], Manoj Kumar S[2*]
[1]Associate Professor, Department of Management Studies and Research Centre, B.M.S. College of Engineering, Bengaluru, Karnataka, India – 560 019.
Email: rsushma.mba@bmsce.ac.in.
ORCID: https://orcid.org/0009-0009-6999-2435
[2]Assistant Professor, Department of MBA, BMS Institute of Technology & Management, Bengaluru, Karnataka, India – 560 119.
Email: manojks@bmsit.in.
ORCID: https://orcid.org/0009-0003-2561-0630
***Corresponding Author**
Manoj Kumar S
Assistant Professor, Department of MBA, BMS Institute of Technology & Management, Bengaluru, Karnataka, India – 560 119.
Email: manojks@bmsit.in.
ORCID: https://orcid.org/0009-0003-2561-0630

ABSTRACT
This study examines the bank-level determinants of profitability in India using a balanced panel of 20 scheduled commercial banks (10 public, 10 private) over 2005–2025 (420 bank-years) drawn from Reserve Bank of India statistics. Because the number of banks is small relative to the number of years, we propose a transparent model-selection protocol and adopt a dynamic two-way fixed-effects estimator as the primary model, with bank-clustered, Driscoll–Kraay and wild-cluster-bootstrap inference, and two-step system GMM with collapsed instruments as a complementary check. Net non-performing assets (NPAs) are the dominant drag on return on assets (short-run coefficient −0.177; long-run −0.236), and the effect is convex, weakening at high NPA levels. Net interest margins are positively related to profitability (0.259), whereas the credit–deposit ratio shows no robust association. Profits are moderately persistent (φ between 0.25 and 0.34). The capital adequacy effect is positive but sensitive to specification and inference. The pass-through of margins to profits is significantly stronger after 2016 (joint F-test p = .002). The NPA penalty is larger for private than for public banks, but the ownership difference is statistically significant only without year effects (p = .041 versus .237 with them). Panel Granger tests indicate feedback between NPAs and profitability, so the estimates are conditional associations rather than causal effects. The findings inform asset-quality supervision and capital policy in bank-dominated emerging economies.
Keywords: Bank profitability; Non-performing assets; Net interest margin; Dynamic panel data; System GMM.
JEL classification: G21; G28; C23; L25

1. INTRODUCTION

Bank profitability matters to shareholders, supervisors and the real economy alike. Retained earnings are the cheapest and most reliable source of bank capital, and in bank-dominated systems persistently weak earnings constrain credit supply and growth (Athanasoglou et al., 2008; Demirgüç-Kunt & Huizinga, 1999). Understanding what moves bank profitability, and whether its drivers differ between state-owned and privately owned banks, is therefore central to prudential policy.

India is an informative setting. Between 2005 and 2025 its banking system passed through rapid credit expansion, global-financial-crisis spillovers, a prolonged deterioration in asset quality that peaked around 2018 (the twin-balance-sheet problem), a regulatory reset comprising the Reserve Bank of India's (RBI) asset quality review and the Insolvency and Bankruptcy Code of 2016, the failure and reconstruction of a large private lender (Yes Bank, 2020), public sector bank amalgamations, the COVID-19 shock and a recovery. In our sample, mean return on assets (ROA) rises from about 0.97% in 2005 to a peak of 1.22% in 2011, falls to −0.06% in 2020 and recovers to 1.25% by 2025, while the mean net NPA ratio moves in the opposite direction, from 0.79% in 2011 to 5.53% in 2018 and back to 0.60% in 2025 (Figure 1).



Source: authors' calculations from RBI data.

Figure 1 Mean ROA, Net NPA Ratio and Net Interest Margin Ratio by Bank Ownership, 2005–2025

Note. Shaded area marks 2016–2020. NPA = net non-performing assets to net advances; NMIR = net interest margin ratio.

Despite a large literature on the determinants of bank profitability (Bourke, 1989; Demirgüç-Kunt & Huizinga, 1999; Dietrich & Wanzenried, 2011; Molyneux & Thornton, 1992; Short, 1979), three gaps remain for India. First, many studies use static fixed- or random-effects models and ignore the cross-sectional dependence that arises when all banks face the same monetary, regulatory and credit cycles. Second, the dynamic nature of profits and the potential endogeneity of NPAs, capital and margins are often ignored or handled with instruments whose validity is untested. Third, evidence on ownership heterogeneity is typically descriptive, comparing mean ratios rather than testing how profitability responds to its drivers.

A related practical question is rarely addressed. The Arellano–Bond and Blundell–Bond generalised method of moments (GMM) estimators were designed for panels with many units and few periods (Arellano & Bond, 1991; Blundell & Bond, 1998; Roodman, 2009a). When banks are fewer than years, the instrument count quickly exceeds the number of units, Hansen tests lose power and can return implausibly perfect *p*-values (Roodman, 2009b), and the Nickell (1981) bias that motivates GMM is small because it is of order $1/T$.

We therefore ask: (i) which bank-level fundamentals explain profitability once bank heterogeneity and common time shocks are removed; (ii) whether their effects differ between public and private banks and changed after the 2016 regulatory reset; and (iii) which estimator suits a bank panel with a small number of banks ($N = 20$) observed over a moderately long period ($T = 21$).

We make three contributions. First, we propose and demonstrate a step-by-step model-selection protocol (Figure 2) that moves from poolability and Hausman–Mundlak tests, through diagnostics for serial correlation, heteroskedasticity and cross-sectional dependence, to a dynamic two-way fixed-effects estimator with three complementary inference strategies suited to few clusters. Second, using the same data, we relate the preferred estimator to pooled, random-effects, static and dynamic fixed-effects, first-difference, difference-GMM and system-GMM alternatives, using the Bond (2002) bracketing argument as a plausibility check. Third, we provide evidence on the determinants of Indian bank profitability across distinct regimes, including formal tests of ownership and post-2016 heterogeneity, a convex asset-quality effect and panel Granger tests of feedback, and show that the capital–profit link and the ownership asymmetry are sensitive to specification and small-cluster inference. Section 2 reviews the literature and develops hypotheses, Section 3 describes the data and method, Section 4 reports results, Section 5 discusses implications, and Section 6 concludes with limitations and future research.

2. Literature Review and Hypotheses Development

2.1 Determinants of Bank Profitability

The structure–conduct–performance and efficient-structure traditions (Bourke, 1989; Short, 1979) framed early work, but the modern approach, following Molyneux and Thornton (1992) and Demirgüç-Kunt and Huizinga (1999), regresses profitability on bank-specific, industry and macroeconomic variables. Athanasoglou et al. (2008) established the standard dynamic specification, in which lagged profitability captures persistence arising from market frictions and informational opacity. Goddard et al. (2004) reached similar conclusions for European banks, and Dietrich and Wanzenried (2011) showed that the relevance of individual determinants differs between crisis and non-crisis periods, which motivates our regime analysis. Asset quality is a recurrent driver: Berger and DeYoung (1997) link problem loans and cost efficiency in both directions, Podpiera and Weill (2008) find that bad loans Granger-cause cost inefficiency in emerging markets, and Louzis et al. (2012) relate bank-specific factors to loan-book quality. Capital is the other classic factor. Berger (1995) reviews the expected-bankruptcy-cost hypothesis, under which better-capitalised banks face lower funding costs and earn more, against moral-hazard and franchise-value arguments (Keeley, 1990) under which the sign can differ; identification is difficult because retained earnings raise capital ratios mechanically.

2.2 Ownership and Banking in India

The Indian ownership literature focuses mostly on efficiency and productivity. Sarkar et al. (1998) and Bhaumik and Dimova (2004) examine whether ownership matters on a relatively level playing field; Bhattacharyya et

al. (1997) and Kumbhakar and Sarkar (2003) study liberalisation and deregulation, with private banks responding better; Sensarma (2006) compares state-owned, private and foreign banks; and Bhaumik and Piesse (2008) show that lending behaviour varies by ownership and is affected by the regulatory treatment of NPAs. Evidence that combines a long recent panel, a dynamic specification, explicit tests of whether slopes differ by ownership and regime, and attention to small-sample inference is scarcer.

2.3 Methodological Background

Dynamic panel models with fixed effects suffer from the Nickell (1981) bias, of order $1/T$. Difference and system GMM (Arellano & Bond, 1991; Arellano & Bover, 1995; Blundell & Bond, 1998) address it with internal instruments but suit large N and small T (Roodman, 2009a). When N is small, instrument proliferation over-fits endogenous variables and weakens the Hansen (1982) test (Roodman, 2009b); Judson and Owen (1999) show that for T of 20 or 30 the least-squares dummy variable (LSDV) estimator performs comparably to or better than GMM. Bond (2002) offers a plausibility check: pooled OLS overstates and the within-groups estimator understates the autoregressive coefficient, so a credible estimate should lie between them. For inference, Driscoll and Kraay (1998) standard errors are robust to cross-sectional dependence when T is not too small (Hoechle, 2007), Petersen (2009) documents the importance of clustering in finance panels, and Cameron et al. (2008) and Cameron and Miller (2015) show that cluster-robust t-tests over-reject with few clusters and recommend the wild cluster bootstrap. Mundlak (1978) provides a Hausman-type test that remains valid under cluster-robust variance estimation.

2.4 Hypotheses Development

Non-performing assets reduce interest income and require provisions charged directly against earnings; the "bad management" and "bad luck" hypotheses (Berger & DeYoung, 1997; Podpiera & Weill, 2008) both imply a negative relationship, although causality may run in both directions. In the dealer model of Ho and Saunders (1981) the interest margin compensates banks for intermediation risk, so a wider margin should raise profit, although the link is partly accounting-driven and potentially endogenous. Well-capitalised banks face lower funding costs and bankruptcy risk (Berger, 1995; Demirgüç-Kunt & Huizinga, 1999), implying a positive effect, whereas the opportunity cost of equity and charter-value incentives (Keeley, 1990) imply a weaker or negative one; given the post-crisis tightening of capital requirements we expect a positive but possibly regime-dependent effect. A higher credit–deposit ratio (CDR) shifts funding towards higher-yielding loans but raises credit and liquidity risk (Berger & Bouwman, 2009), so the sign is ambiguous and we hypothesise a positive net effect. Informational opacity and earnings smoothing make current profits depend on past profits (Athanasoglou et al., 2008; Berger et al., 2000). Public banks operate under implicit sovereign support, priority-sector mandates and weaker market discipline, whereas private banks face shareholder pressure and may provision more aggressively, so slopes, particularly for NPA and CAR, should differ. Finally, the 2016 asset quality review and Insolvency and Bankruptcy Code changed the recognition and resolution of stressed assets, which may have altered how margins, capital and NPAs map into earnings (Dietrich & Wanzenried, 2011). We test:

H1: Net NPAs are negatively related to ROA.
H2: The net interest margin ratio (NMIR) is positively related to ROA.
H3: The capital adequacy ratio (CAR) is positively related to ROA.
H4: The credit–deposit ratio (CDR) is positively related to ROA.
H5: Lagged ROA has a positive coefficient that is less than one.
H6: The effects of the bank-level determinants of ROA, in particular NPA and CAR, differ between public and private sector banks.
H7: The relationships between ROA and its determinants changed after 2016.

3. DATA AND EMPIRICAL STRATEGY

3.1 Data and Variables

The data are a balanced panel of 20 scheduled commercial banks observed annually over 2005–2025 (21 years; 420 bank-years), compiled from the RBI's *Select Ratios of Scheduled Commercial Banks*. The panel comprises ten public sector banks (State Bank of India, Bank of Baroda, Bank of India, Canara Bank, Central Bank of India, Indian Bank, Indian Overseas Bank, Punjab National Bank, UCO Bank and Union Bank of India) and ten private sector banks (Axis Bank, City Union Bank, Federal Bank, HDFC Bank, ICICI Bank, IndusInd Bank, Karnataka Bank, Kotak Mahindra Bank, South Indian Bank and Yes Bank). The year variable follows the labelling of the RBI source. The only missing values are the net NPA ratio of Yes Bank for 2005–2007, so static models that include NPA use 417 bank-years and dynamic models use 398 (one year is lost to the lag). Retaining banks that experienced distress (Yes Bank, Indian Overseas Bank and UCO Bank) mitigates survivorship bias within the sampled banks, although the sample is not the full population of Indian banks.

The dependent variable is ROA (net profit to average total assets, %). The regressors are the credit–deposit ratio (CDR, loans to deposits), the net interest margin ratio (NMIR), the capital adequacy ratio (CAR, regulatory capital to risk-weighted assets) and the ratio of net NPAs to net advances (NPA). All variables are in percentage units, so coefficients are percentage-point effects. PUB (1 for public sector banks) and POST (1 from 2016 onward, the asset quality review and Insolvency and Bankruptcy Code regime) are used in interaction specifications, and COVID (1 for 2020–2021) is a control in the GMM models. The data contain no macroeconomic or bank-size variables; common macroeconomic shocks are absorbed by year effects or regime dummies (see Section 6). Definitions and expected signs are in Table 1.

Table 1 Variable Definitions and Expected Signs

Variable	Definition	Role	Expected sign
ROA	Return on assets (net profit to average total assets)	Dependent	—
NPA	Net NPAs to net advances	Regressor	− (H1)
NMIR	Net interest margin ratio	Regressor	+ (H2)
CAR	Capital adequacy ratio (regulatory capital to risk-weighted assets)	Regressor	+ (H3)
CDR	Credit–deposit ratio (loans to deposits)	Regressor	+ (H4)
PUB	Dummy: 1 = public sector bank	Moderator	Differential (H6)
POST	Dummy: 1 for 2016 onward	Moderator / control	Differential (H7)
COVID	Dummy: 1 for 2020–2021	Control (GMM)	−

Note. Definitions follow the RBI source, *Select Ratios of Scheduled Commercial Banks*. NPA is missing for Yes Bank in 2005–2007.

3.2 Empirical Models

Let $i = 1, \ldots, 20$ index banks and $t = 2005, \ldots, 2025$ index years. The static specification is

$$ROA_{it} = \alpha_i + \beta_1 CDR_{it} + \beta_2 NMIR_{it} + \beta_3 CAR_{it} + \beta_4 NPA_{it} + \varepsilon_{it} \quad (1)$$

where α_i captures time-invariant bank heterogeneity (business model, franchise, ownership). Equation 1 is estimated by pooled OLS, random effects, fixed effects and two-way fixed effects (adding year effects λ_t). Because profits are persistent and the regressors are plausibly determined jointly with profitability, the dynamic specification is

$$ROA_{it} = \varphi\, ROA_{i,t-1} + x'_{it}\beta + \alpha_i + \lambda_t + \varepsilon_{it} \quad (2)$$

where x_{it} = (CDR, NMIR, CAR, NPA). Year effects absorb common shocks such as the interest-rate cycle, the 2016 reset and the pandemic without requiring a choice among noisy macroeconomic proxies. The long-run effect of regressor k is $\beta_k/(1 - \varphi)$, with delta-method standard errors. For the GMM estimators, year effects are replaced by two regime dummies to keep the instrument count below the number of banks:

$$ROA_{it} = \alpha + \varphi\, ROA_{i,t-1} + x'_{it}\beta + \delta_1 POST_t + \delta_2 COVID_t + \mu_i + \varepsilon_{it} \quad (3)$$

Heterogeneity is tested by interacting each regressor with an indicator D (PUB or POST) and testing the joint significance of the four interaction coefficients:

$$ROA_{it} = \varphi\, ROA_{i,t-1} + \Sigma_k \beta_k x_{k,it} + \Sigma_k \gamma_k (D \times x_{k,it}) + \alpha_i + \lambda_t + \varepsilon_{it} \quad (4)$$

The level of PUB is absorbed by the bank effects and the level of POST by the year effects. A static version of Equation 4, without the lagged dependent variable and year effects, is also estimated.

3.3 Model-Selection Protocol and Choice of Dynamic Estimator

We follow the six-step protocol summarised in Figure 2, in which each step is a testable decision reported in Section 4.2. (1) Poolability is assessed with F-tests on bank effects and, conditional on bank effects, on year effects. (2) Fixed versus random effects is assessed with the Hausman (1978) test and a cluster-robust Mundlak (1978) test that adds bank means of the regressors to a random-effects model. (3) Residual diagnostics comprise the Wooldridge first-difference serial-correlation test (Drukker, 2003), the modified Wald groupwise heteroskedasticity test and the Pesaran (2021) CD test. (4) Stationarity is examined with the Maddala and Wu (1999) Fisher-type augmented Dickey–Fuller (ADF) test and the cross-sectionally augmented CIPS test (Pesaran, 2007), whose critical values for $N = 20$ and $T = 21$ are simulated (2,000 replications) under a driftless random-walk null; given the short time dimension we interpret unit-root results cautiously. (5) The dynamic estimator is chosen as described next. (6) Inference and robustness follow Sections 3.4 and 4.7.

With $N = 20$ and $T = 21$, the Nickell bias is approximately $-(1 + \varphi)/(T - 1)$, or about −0.07 for our estimate of φ, and it falls as T grows. A system GMM estimator using lags 2–3 of the endogenous variables produces 33 instruments for only 20 banks and a Hansen statistic of essentially zero with $p = 1.000$ (Appendix A), the signature of instrument proliferation (Roodman, 2009b). A "lean" system GMM with collapsed instruments uses 12 instruments, fewer than the number of banks, and is retained as a robustness check. In the GMM models, lagged ROA and the four bank-level regressors are treated as endogenous, POST and COVID as exogenous, and standard errors use the Windmeijer (2005) finite-sample correction; validity is assessed with the Arellano–Bond AR(1) and AR(2) tests and the Hansen test. We therefore choose LSDV (dynamic two-way fixed effects) as the primary estimator and use pooled OLS, within-groups and GMM estimates to bracket φ (Bond, 2002).

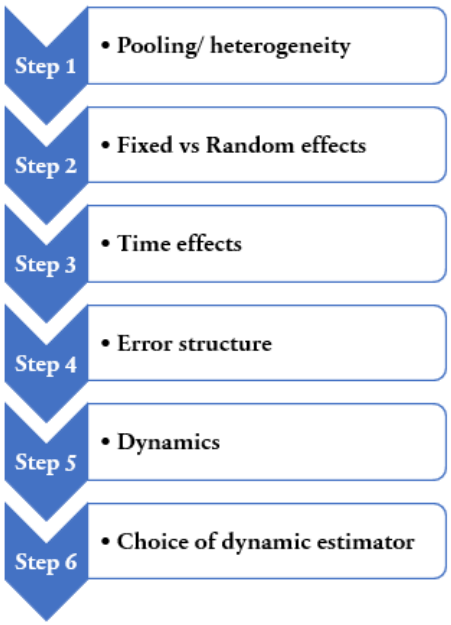


Figure 2 Model-Selection Protocol for a Bank Panel With $N = 20$ and $T = 21$. *Source:* authors' own creation

.3.4 Inference, Heterogeneity and Robustness

We report three complementary inference strategies: (a) bank-clustered standard errors with the CR1 small-sample correction, evaluated against a t distribution with $G - 1 = 19$ degrees of freedom; (b) Driscoll and Kraay (1998) standard errors with a Bartlett kernel; and (c) restricted wild cluster bootstrap p-values (Cameron et al., 2008) with Rademacher weights (2,999 replications for the preferred dynamic model and 999 for static models). Where the strategies disagree, we treat the bootstrap as the most reliable guide for a panel with 20 clusters. Granger-type predictive relationships are examined with the Dumitrescu and Hurlin (2012) test, which allows heterogeneous coefficients across banks. Heterogeneity is examined by interacting the regressors with PUB and POST, by estimating public and private sub-samples, and by adding quadratic terms in CAR and NPA. Robustness checks are 1%/99% winsorisation; excluding Yes Bank (reconstructed in 2020); excluding the three distressed banks; excluding the six public banks most affected by the 2017–2020 mergers (State Bank of India, Bank of Baroda, Punjab National Bank, Canara Bank, Union Bank of India and Indian Bank); lagging the regressors one year; excluding 2016–2020; and a first-difference estimator. Estimation was carried out in Python (linear models, stats models, pydynpd and NumPy).

4. RESULTS

4.1 Descriptive Statistics

Table 2 summarises the data. Mean ROA is 0.86% with substantial dispersion (SD = 0.85) and a heavy left tail (skewness = −1.86); the minimum, −5.39%, is Yes Bank in 2020. The NPA ratio is strongly right-skewed (skewness = 2.47), with a maximum of 15.33% for Indian Overseas Bank in 2018. Jarque–Bera tests reject normality for all variables ($p < .001$), which supports robust inference and winsorisation checks. Ownership comparisons use the ten bank-level means per group to avoid treating serially dependent bank-years as independent; Mann–Whitney tests give the same conclusions (all $p < .005$). Private banks are markedly more profitable (ROA of 1.25% versus 0.48%), earn wider margins, hold more capital and lend more per unit of deposits, while public banks carry NPA ratios more than twice as high. ROA correlates strongly and negatively with NPA ($r = -.79$) and positively with NMIR ($r = .63$) and CAR ($r = .53$); variance inflation factors range from 1.31 to 1.57, so multicollinearity is not a concern.

Table 2 Descriptive Statistics and Ownership Comparison

Variable	N	Mean	SD	Min	Max	Skew.	Private mean (SD)	Public mean (SD)	Welch t p
ROA (%)	420	0.864	0.845	−5.390	2.650	−1.864	1.250 (0.739)	0.478 (0.766)	< .001
CDR (%)	420	75.111	12.054	44.900	162.715	1.178	80.78 (12.84)	69.44 (7.86)	.002
NMIR (%)	420	2.850	0.713	1.075	5.618	0.745	3.17 (0.77)	2.53 (0.47)	.012
CAR (%)	420	14.406	2.773	8.460	23.750	0.662	15.68 (2.85)	13.13 (2.00)	< .001
NPA (%)	417	2.090	2.313	0.010	15.330	2.465	1.24 (1.10)	2.93 (2.83)	< .001

Note. Columns 2–7 use the full sample (20 banks, 2005–2025; NPA has three missing observations). The last three columns compare the ten private and ten public banks using bank-level means (Welch t-test).

4.2 Panel Diagnostics and Model Choice

Pooled OLS is rejected in favour of bank effects, $F(19, 393) = 4.61$, $p < .001$, and year effects are jointly significant

given bank effects, $F(20, 373) = 6.23$, $p < .001$. Both the Hausman test, $\chi^2(4) = 18.39$, $p = .001$, and the cluster-robust Mundlak test, $\chi^2(4) = 20.97$, $p < .001$, reject random effects. Fixed-effects residuals show significant serial correlation (Wooldridge $F(1, 19) = 23.89$, $p < .001$), groupwise heteroskedasticity (modified Wald $\chi^2(20) = 2{,}046.9$, $p < .001$) and strong cross-sectional dependence (Pesaran CD = 12.30, mean $\rho = 0.19$, $p < .001$), the last of which is expected in a banking system exposed to common cycles and policy shocks. Fixed and time effects are therefore needed and conventional standard errors are invalid, which motivates clustered, Driscoll–Kraay and bootstrap inference.

Dependence is also pervasive in the raw series (Pesaran CD from 7.64 for NMIR to 34.62 for CAR, all $p < .001$), so bank-clustered errors alone are inadequate. The unit-root evidence is mixed: the Fisher-type ADF test, which assumes independence across banks, fails to reject a unit root for ROA, CAR and NPA, whereas the CIPS test, which accounts for common factors, rejects for ROA and NPA and is borderline for CAR and NMIR; only CDR looks consistently non-stationary. All variables are stationary in first differences ($p < .001$). With only 21 annual observations per bank, these tests have limited power and are sensitive to lag selection, so we treat the series as highly persistent rather than strictly integrated, estimate dynamic models, and confirm the main signs in first differences (Section 4.7). Spurious-regression concerns are further mitigated because all variables are bounded ratios and bank and year effects remove level differences and common trends.

4.3 Baseline and Dynamic Estimates

Table 3 presents seven estimators. The signs of NMIR (positive), NPA (negative) and CAR (positive) are stable across all specifications, whereas CDR is negative but weak. The NPA coefficient falls from about −0.22 in the static models to between −0.15 and −0.18 once lagged ROA is included, as expected when persistence absorbs part of the contemporaneous association. For the static fixed-effects model, Driscoll–Kraay standard errors are 0.032 (NPA), 0.046 (NMIR), 0.019 (CAR) and 0.008 (CDR), and wild cluster bootstrap p-values are 0.001, 0.006, 0.214 and 0.791; the capital coefficient is therefore marginal and does not survive small-cluster correction in the static model. Standardised fixed-effects coefficients indicate that NPA is the dominant driver ($\beta = -0.61$ standard deviations), followed by NMIR (0.22), CDR (−0.19, insignificant) and CAR (0.12). A one within-bank standard deviation increase in NPA (2.04 percentage points) is associated with a 0.45 percentage point fall in ROA, about two-thirds of the within-bank standard deviation of ROA (0.68).

The dynamic estimates place φ at 0.36 in the within-groups model and 0.25 once year effects are added; the pooled OLS estimate is 0.41. The lean system GMM estimate (0.38) lies inside the Bond (2002) bracket defined by the within-groups (0.36) and pooled (0.41) estimates, both of which, like the lean GMM, omit year dummies. This supports its plausibility, although its inference is less reliable than that of the LSDV estimates.

Table 3 Determinants of ROA: Static and Dynamic Panel Estimates

	(1) Pooled OLS	(2) Random effects	(3) Fixed effects	(4) Two-way FE	(5) Dynamic FE	(6) Dynamic two-way FE	(7) System GMM (lean)
ROA(t−1)	—	—	—	—	0.356*** (9.41)	0.250*** (3.39)	0.384*** (6.19)
CDR	−0.006 (−0.49)	−0.010 (−0.82)	−0.013 (−1.02)	−0.016 (−1.27)	−0.018 (−1.50)	−0.019 (−1.69)	−0.015 (−1.47)
NMIR	0.347*** (6.14)	0.317*** (6.67)	0.263*** (3.56)	0.273** (2.79)	0.220** (2.83)	0.259** (2.61)	0.259*** (3.05)
CAR	0.049* (2.00)	0.042* (1.78)	0.036 (1.56)	0.068* (2.03)	0.049** (2.31)	0.071* (2.08)	0.056** (2.03)
NPA	−0.220*** (−13.02)	−0.220*** (−13.16)	−0.222*** (−12.99)	−0.222*** (−7.32)	−0.154*** (−11.88)	−0.177*** (−6.48)	−0.094*** (−2.91)
Observations	417	417	417	417	398	398	377
R^2	0.720	0.713	0.644	0.592	0.721	0.641	—
Bank effects	No	Random	Yes	Yes	Yes	Yes	Differenced
Year effects	No	No	No	Yes	No	Yes	No
Instruments / Hansen p	—	—	—	—	—	—	12 / .17
AR(2) p	—	—	—	—	—	—	.84

Note. Dependent variable: ROA (%). t-statistics in parentheses (bank-clustered, CR1 correction; p-values from t with 19 degrees of freedom; z for GMM). Constants not reported. R^2 is the pooled or overall R^2 in columns 1–2 and the R^2 after removing the effects in columns 3–6. Column 7: two-step system GMM, collapsed instruments (lags 2–3 of ROA and NPA, lag 2 of NMIR and CAR, CDR exogenous), Windmeijer-corrected standard errors. *$p < .10$. **$p < .05$. ***$p < .01$.

4.4 Preferred Model: Dynamic Two-Way Fixed Effects

Column 6 of Table 3 is our preferred specification, and Table 4 reports its coefficients under the three inference strategies. ROA is persistent: a one-percentage-point ROA

in the previous year is associated with 0.25 percentage points of ROA today (bootstrap $p < .001$), implying a long-run multiplier of 1.33, which supports H5. NPA is the dominant determinant: each one-percentage-point increase in the net NPA ratio lowers ROA by 0.177 percentage points in the short run and 0.236 in the long run (all three approaches, $p < .001$), supporting H1. Because the sample SD of NPA is 2.31, a one-SD rise in NPA is associated with a 0.41 percentage point lower ROA in the short run and 0.55 in the long run, against a mean ROA of 0.86%. The net interest margin has a coefficient of 0.259 (long run 0.346), significant at the 5% level under clustered and Driscoll–Kraay inference ($p = .017$) and marginally so under the wild cluster bootstrap ($p = .056$), supporting H2. CAR has a coefficient of 0.071 (long run 0.094), with a clustered p of .051 and a bootstrap p of .037, a modest but fairly consistent association that gives partial support to H3. CDR is negative (−0.019) and imprecisely estimated (bootstrap $p = .444$), so we find no robust evidence that pushing credit further beyond deposits raises profitability; H4 is not supported.

Table 4 Preferred Model: Inference, Long-Run Effects and Economic Magnitude

Variable	Coefficient	Cluster t	D–K t	Cluster p	Wild bootstrap p	Long-run effect (SE)	+1 SD effect on ROA, short / long run
ROA(t−1)	0.250***	3.39	3.79	.003	< .001	1.33× (multiplier)	—
CDR	−0.019	−1.69	−2.24	.107	.444	−0.025* (0.013)	−0.23 / −0.30
NMIR	0.259**	2.61	5.11	.017	.056	0.346*** (0.108)	0.18 / 0.25
CAR	0.071*	2.08	2.03	.051	.037	0.094** (0.040)	0.20 / 0.26
NPA	−0.177***	−6.48	−6.75	< .001	< .001	−0.236*** (0.027)	−0.41 / −0.55

Note. Dynamic two-way FE, 398 bank-years, 20 clusters. Stars refer to bank-clustered p-values (t with 19 degrees of freedom). D–K = Driscoll–Kraay. Long-run effect = $\beta/(1-\varphi)$, with delta-method standard errors; for ROA(t−1) the entry is the long-run multiplier $1/(1-\varphi)$. SD effects use the overall sample SDs in Table 2. Wild bootstrap: restricted, Rademacher weights, 2,999 replications. *p < .10. **p < .05. ***p < .01.

As an illustration, mean NPA rose from 0.91% in 2010 to 5.53% in 2018, an increase of 4.62 percentage points; multiplied by the long-run NPA coefficient this is about −1.09 percentage points of ROA, of the same order as the observed fall in mean ROA from 1.19% to 0.07%. This is an accounting illustration, not a causal decomposition, because the model contains year effects that absorb common movements.

4.5 Complementary Evidence From System GMM

Appendix A reports GMM estimates that treat lagged ROA and the bank-level regressors as endogenous. The baseline two-step system-GMM model (collapsed instruments, lag 2; POST and COVID exogenous) passes its specification tests: there is first-order but no second-order serial correlation (AR(2) $p = .83$), and the Hansen test does not reject instrument validity ($p = .151$) with 13 instruments for 20 banks. The persistence coefficient of 0.336 lies inside the Bond (2002) bounds formed by the dynamic fixed-effects (0.297) and dynamic pooled-OLS (0.362) estimates from the same specification, so about two-thirds of a shock to ROA dissipates within a year, again supporting H5. NMIR (short run 0.29; long run 0.44) and NPA (−0.08; long run −0.12) remain highly significant when endogeneity is accounted for. CAR is positive and significant in all GMM columns (0.06 to 0.07, $p < .05$), in contrast to its fragility in the static models, while CDR remains insignificant. The POST coefficient (−0.23) indicates that, conditional on the drivers, profitability was about 0.2 percentage points lower after 2016.

Two cautions apply. First, the GMM NPA coefficient is smaller in absolute value than the fixed-effects estimates (−0.08 to −0.12 versus −0.18 to −0.22); this is expected when lagged profit absorbs part of the persistence in NPA-driven losses and when simultaneity between earnings and provisioning is addressed, but it shows that magnitudes are model-dependent. Second, the Hansen test in the wider-instrument specification (18 instruments for 20 banks) rejects at the 5% level ($p = .040$), a symptom of instrument proliferation (Roodman, 2009b) that we avoid in the baseline. With $T \geq N$, GMM estimates should be read as supporting rather than replacing the fixed-effects evidence.

4.6 Heterogeneity: Ownership, the Post-2016 Regime and Non-Linearity

Ownership. Table 5 (column 1) reports interaction models in the dynamic two-way fixed-effects framework. Allowing all four slopes to differ for public banks does not produce a jointly significant difference, $F(4, 19) = 1.52$, $p = .237$. The point estimates nonetheless suggest that private banks' profits react more strongly to NPAs (−0.278 against −0.177 for public banks), a pattern also visible in the dynamic sub-samples (−0.283 for private and −0.131 for public banks; with only ten clusters each, p-values should be read cautiously). In the static fixed-effects model without year effects the contrast is sharper: the NPA coefficient is −0.342 for private and −0.191 for public banks, a difference of 0.151 ($p = .006$), and the joint Wald test rejects common slopes, $\chi^2(4) = 9.94$, $p = .041$. H6 is therefore supported in the static specification but not established once year effects and dynamics are included; the evidence is best described as suggestive for NPA and specification-dependent overall. Other ownership contrasts are not robust: in the static model capital is associated with higher profits only among private banks (0.060 versus 0.005 for public banks), but in the dynamic sub-samples both coefficients are positive and weakly significant (0.057 for public and 0.080 for private banks). One interpretation of the stronger private-bank sensitivity to NPAs is that private banks, subject to equity-market discipline, recognise and provision for stressed

assets more promptly, whereas public banks, backed by sovereign ownership, may have smoothed the earnings impact through forbearance and recapitalisation. We present this as a conjecture: the data contain no provisioning or funding-structure variables.

Post-2016 regime. The post-2016 interactions are jointly highly significant in the dynamic model, $F(4, 19) = 6.48$, $p = .002$, which supports H7 (Table 5, column 2). The most striking change is the margin: the NMIR coefficient rises from 0.215 before 2016 to 0.513 from 2016 onward (0.263 to 0.601 in the static split sample). The NPA slope becomes less negative (from −0.225 to −0.137; −0.233 to −0.127 in the static split), the CAR slope rises (from 0.007 to 0.115; 0.020 to 0.084 in the static split), and the CDR slope turns negative (−0.027 in the dynamic model). A plausible reading, presented as a conjecture, is that once large stocks of stressed assets were recognised and provisioned, a given margin translated more fully into earnings and NPA formation became a smaller marginal drag. The post-period includes only 200 bank-years, and sub-sample estimates should be read with that in mind.

Table 5 Heterogeneity: Ownership and Post-2016 Interactions (Dynamic Two-Way FE)

	(1) Interaction with public-bank indicator	(2) Interaction with post-2016 indicator
ROA(t−1)	0.204** (2.58)	0.216*** (4.73)
CDR	−0.020 (−1.50)	0.000 (0.11)
NMIR	0.247* (2.06)	0.215** (2.60)
CAR	0.080** (2.23)	0.007 (0.41)
NPA	−0.278*** (−4.56)	−0.225*** (−6.76)
CDR × indicator	0.018 (1.32)	−0.027* (−2.01)
NMIR × indicator	0.012 (0.10)	0.299*** (3.73)
CAR × indicator	−0.033 (−0.94)	0.108* (1.88)
NPA × indicator	0.100* (1.74)	0.088** (2.14)
Joint F-test, four interactions (p)	$F = 1.52$ (.237)	$F = 6.48$ (.002)
Observations	398	398

Note. Dynamic two-way FE with bank-clustered t-statistics in parentheses (19 degrees of freedom). In column 1 the indicator equals 1 for public sector banks (level absorbed by bank effects); in column 2 it equals 1 for years ≥ 2016 (level absorbed by year effects). Main-effect rows show the slope for private banks (column 1) and for 2005–2015 (column 2). *p < .10. **p < .05. ***p < .01.

Non-linearity. The NPA effect is convex. In the dynamic two-way model the quadratic term is positive (0.007, t = 2.58), so the marginal effect of an extra point of NPA shrinks from −0.23 at NPA = 1% to −0.11 at NPA = 10%, with an implied turning point (about 17.8%) outside most of the sample range; the joint test of the two quadratic terms gives $F = 3.76$, $p = .042$. The static fixed-effects model gives the same message: the NPA coefficient is −0.328 and the NPA² coefficient is +0.010 (p < .001), implying a marginal effect of −0.29 at the sample-mean NPA ratio (2.1%) but only −0.12 at 10%. The earnings penalty is steepest when asset quality begins to deteriorate and flattens once banks are already deeply impaired, consistent with front-loaded provisioning and with profits approaching a floor when interest income on the affected assets has already been lost. The quadratic term in CAR is not significant in either framework, so there is no evidence of an interior optimum in capital within the observed range.

4.7 Robustness

Table 6 shows that the main conclusions are stable. The NPA coefficient lies between −0.150 and −0.179 across the five dynamic checks and is significant at the 1% level in all of them; the NMIR coefficient lies between 0.211 and 0.232; and CAR remains positive throughout, though its significance varies. Excluding Yes Bank and the six merger-affected public banks leaves the picture unchanged, which suggests that neither an extreme observation nor the 2017–2020 consolidation drives the results. Lagged regressors, which mitigate simultaneity, retain negative NPA and positive NMIR effects, although the persistence coefficient is smaller and less precise. The first-difference estimator, which is robust to unit-root concerns, gives NPA = −0.178, NMIR = 0.334 and CAR = 0.097 (all significant at 5%). The CDR coefficient is small and statistically insignificant in most specifications. Appendix B reports the same exercise for the static fixed-effects model: it gives NMIR of 0.22 to 0.28 and NPA of −0.18 to −0.23, stable in sign, magnitude and significance, whereas the CAR coefficient is significant only when the regressors are lagged or differenced and is indistinguishable from zero under winsorisation or when Yes Bank is removed. This pattern, together with the static-model bootstrap p-value of .214, is why we characterise the capital–profit link as suggestive but not robust.

Table 6 Robustness Checks (Dynamic Two-Way FE Unless Stated)

	(1) Winsorised 1/99%	(2) Excl. Yes Bank	(3) Excl. merger-affected banks	(4) Lagged regressors	(5) Excl. 2016–2020	(6) First differences
ROA($t-1$)	0.299*** (5.06)	0.291*** (3.42)	0.263** (2.95)	0.127 (1.47)	0.284*** (4.21)	—
CDR	−0.006 (−1.10)	−0.000 (−0.04)	−0.020* (−1.85)	−0.013** (−2.20)	−0.005 (−0.95)	−0.028 (−1.62)
NMIR	0.219*** (2.99)	0.211** (2.86)	0.232* (2.03)	0.228** (2.64)	0.224*** (3.04)	0.334** (2.37)
CAR	0.043** (2.13)	0.025* (2.00)	0.074* (1.97)	0.023 (1.69)	0.023** (2.15)	0.097*** (3.08)
NPA	−0.169*** (−9.58)	−0.150*** (−12.36)	−0.179*** (−5.31)	−0.174*** (−10.59)	−0.169*** (−5.38)	−0.178*** (−4.28)
Observations	398	380	278	397	298	397
Clusters	20	19	14	20	20	20

Note. Bank-clustered *t*-statistics in parentheses. In column 4 all regressors other than lagged ROA are lagged one year. Column 6 is a first-difference regression with year effects, so there is no lagged dependent variable. *p < .10. **p < .05. ***p < .01.

4.8 Panel Granger Causality

Table 7 reports Dumitrescu–Hurlin tests (one lag, $T = 21$), which allow coefficients to differ across banks, show that past NMIR, CAR and especially NPA help predict future ROA ($\bar{W} = 2.14$, 2.53 and 10.46, respectively; for NPA, $\tilde{Z} = 23.82$, $p < .001$), whereas CDR has no predictive power ($p = .162$).

Table 7 Dumitrescu–Hurlin Panel Granger Non-Causality Tests (One Lag)

Direction	W̄	$\tilde{Z}$ (small-sample)	p	Inference
CDR → ROA	1.67	1.40	.162	No predictive power
NMIR → ROA	2.14	2.60	.009	Granger-causes
CAR → ROA	2.53	3.57	< .001	Granger-causes
NPA → ROA	10.46	23.82	< .001	Granger-causes
ROA → CDR	4.43	8.44	< .001	Granger-causes
ROA → NMIR	0.82	−0.79	.430	No predictive power
ROA → CAR	1.46	0.86	.390	No predictive power
ROA → NPA	2.80	4.28	< .001	Granger-causes

Note. H_0: *x* does not Granger-cause *y* for any bank. $\tilde{Z}$ uses the small-T standardisation of Dumitrescu and Hurlin (2012) with $T = 21$ and one lag.

NPA and ROA also exhibit reverse predictability (ROA → NPA, $\bar{W} = 2.80$, $p < .001$), consistent with a feedback loop in which weak earnings reduce the ability to write off and provision, and bad loans in turn depress earnings. Profitability also predicts the credit–deposit ratio ($\bar{W} = 4.43$, $p < .001$), in line with profitable banks expanding their lending, but not NMIR ($p = .430$) or CAR ($p = .390$), which supports treating capital as a predetermined driver of earnings. These findings are predictive rather than structural, and they reinforce our reading of the coefficients as conditional associations.

4.9 Summary of Hypothesis Tests

Table 8 summarises the evidence. H1, H2, H5 and H7 are supported; H3 and H6 are supported only partially and in a specification-dependent way; H4 is not supported.

Table 8 Summary of Hypothesis Tests

Hypothesis	Evidence
H1: NPA lowers ROA	−0.177; bootstrap $p < .001$; negative in all specifications
H2: NMIR raises ROA	0.259; bootstrap $p = .056$ (dynamic) and .006 (static)
H3: CAR raises ROA	0.071; bootstrap $p = .037$ (dynamic) but .214 (static)
H4: CDR raises ROA	−0.019; bootstrap $p = .444$
H5: Persistence	$\varphi = 0.25$ (dynamic two-way FE); 0.336 (system GMM)
H6: Ownership differences	Joint F $p = .237$ (dynamic); Wald $p = .041$ (static)
H7: Post-2016 change	Joint F $p = .002$

Note. Estimates from Table 3, column 6, and Table 4; heterogeneity tests from Section 4.6; GMM estimates from Appendix A.

5. DISCUSSION

The evidence supports H1, H2, H5 and H7, gives partial and specification-dependent support to H3 and H6, and does not

support H4 (Table 8). The NPA ratio has a large, precisely estimated negative effect on ROA in every specification (about −0.22 in static models, −0.18 in the preferred dynamic model and −0.08 to −0.12 in GMM models), and the penalty is convex. This is consistent with international evidence linking problem loans to weak earnings and cost inefficiency (Berger & DeYoung, 1997; Podpiera & Weill, 2008) and with the Indian experience of 2015–2020, when provisioning absorbed a large share of operating income at the most stressed banks. The smaller GMM coefficient is what one expects if part of the fixed-effects association reflects simultaneity between earnings and provisions, as the Granger tests also suggest; we therefore treat the dynamic fixed-effects estimate as the central estimate and the GMM estimates as a lower bound for the NPA effect.

The positive and stable margin coefficient (0.22 to 0.35 across specifications) is consistent with the dealer-model view that the interest margin is the main source of bank earnings (Ho & Saunders, 1981), although the relationship is partly accounting-driven. The post-2016 rise in margin pass-through is the most novel empirical result. It need not mean that margins became more important in an economic sense; it may reflect the weaker mechanical offset from provisions once the stress cycle had passed, or retail-heavy loan growth. Either way, a single time-invariant coefficient is a poor summary of two decades, which argues for period-specific effects or a structural-change test whenever a panel spans a regulatory reset (Dietrich & Wanzenried, 2011).

Capital is positive in every specification and significant in the dynamic and GMM models, but it does not survive bootstrap inference in the static model, winsorisation or the exclusion of Yes Bank. This fragility is unsurprising given the identification difficulty noted by Berger (1995) and the opposing expected-bankruptcy-cost and franchise-value arguments (Keeley, 1990). The Granger tests suggest that CAR does not respond to lagged ROA, which is consistent with treating capital as predetermined, but they do not resolve endogeneity; we read the capital effect as modest and not robust.

Private banks' earnings appear more sensitive to NPAs than public banks' in every specification, in line with Indian evidence that public and private banks respond differently to deregulation and to the regulatory treatment of NPAs (Bhaumik & Dimova, 2004; Bhaumik & Piesse, 2008; Kumbhakar & Sarkar, 2003; Sensarma, 2006). Statistical significance, however, depends on the specification ($p = .041$ without year effects, .237 with them), the mechanisms cannot be tested with our data, and with ten banks per group sub-sample inference is limited. Profits are persistent ($\varphi \approx 0.25$ in the preferred model; 0.34 in the baseline GMM model; Nickell-corrected values plausibly around 0.32), but less so than often reported for stable advanced-economy samples (Berger et al., 2000; Goddard et al., 2004), which is consistent with an emerging-market, crisis-affected sample in which large asset-quality shocks are worked off quickly.

Methodologically, the bracket around φ formed by pooled OLS (0.41) and within-groups (0.36) is narrow, the Nickell bias is small, and the GMM instrument count is high relative to N. The most defensible approach for a bank panel with N close to or below T is therefore a dynamic fixed-effects model with small-cluster inference, with collapsed-instrument GMM as a robustness check; a more complicated estimator is not necessarily the safer one (Judson & Owen, 1999; Roodman, 2009b).

5.1 Implications

The results reinforce the value of early asset-quality recognition. Each percentage point of net NPA is associated with roughly a quarter of a percentage point of ROA in the long run, and the marginal profit loss from an additional NPA is largest at low NPA levels, which supports forward-looking provisioning and early-warning frameworks rather than reliance on late-stage resolution. If the ownership asymmetry in the NPA penalty is confirmed in larger samples, uniform stress-test calibrations may understate the earnings vulnerability of private banks to credit shocks. Sustainable margins and asset quality are more closely tied to profitability than loan-to-deposit expansion, which cautions against growth strategies that push credit beyond deposits without attention to credit quality. The dominance of the margin channel implies that policies compressing spreads, for example administered-rate transmission or competitive pricing pressure, have first-order implications for bank earnings and hence internal capital generation, while the weak and specification-dependent link between capital and profitability cautions against expecting higher regulatory ratios or capital injections alone to restore earnings.

6. CONCLUSION, LIMITATIONS AND FUTURE RESEARCH

Using a balanced panel of 20 Indian banks over 2005–2025, we show that a dynamic two-way fixed-effects specification with cluster-robust, Driscoll–Kraay and wild-bootstrap inference is a defensible primary estimator when the number of banks is small and the time dimension is moderate, and that system GMM is best treated as a robustness check rather than the default. Net NPA is the strongest determinant of ROA, and its effect is convex; the net interest margin follows; capital adequacy is positive but not robust; the credit–deposit ratio shows no robust effect; and profits are moderately persistent. Margin pass-through to profits is significantly higher after 2016. Public–private differences, concentrated in the NPA slope, are suggestive and depend on the specification. Granger tests indicate feedback between NPAs and profitability, so the estimates should be read as conditional associations rather than strict causal effects.

Several limitations should be noted. First, the sample includes only 20 surviving banks; banks merged or closed before 2025 and newer private, small finance and foreign banks are excluded, so the results describe incumbents rather than the whole system. Second, merger-related discontinuities, including the 2017–2020 public sector amalgamations and the 2023 merger of HDFC Bank with its parent, are only partly absorbed by bank and year effects, although excluding merger-affected banks does not change the results. Third, NMIR and CAR are plausibly endogenous to ROA (margins are a component of profit; retained earnings raise capital); lags, first differences and GMM address this but do not amount to a fully identified causal design. Fourth, the data contain no macroeconomic controls (GDP growth, inflation, policy rate) or bank-level controls (size, cost-to-income ratio, diversification, funding mix, provisioning), so omitted-variable bias cannot be excluded. Fifth, with 20 banks and 21 periods, system GMM operates at the edge of its asymptotics, and the unit-root tests and ownership sub-sample estimates have limited power. Sixth, the year variable follows the labelling of the RBI source and may refer to financial rather than calendar years.

Future work could extend the panel to more banks and add macroeconomic and market-structure controls, use provisioning and funding data to test the mechanisms behind ownership differences, apply bias-corrected LSDV estimators (Everaert & Pozzi, 2007; Kiviet, 1995), use panel quantile or threshold models to study heterogeneity across the ROA and NPA distributions, or use panel VAR to model the joint dynamics of asset quality, capital and profitability.

Declarations

Funding. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Conflicts of interest. The authors declare no conflict of interest.

Data availability. The panel is compiled from the RBI's Select Ratios of Scheduled Commercial Banks. The compiled dataset and the estimation code are available from the corresponding author on request.

Author contributions (CRediT). R Sushma: Conceptualisation; Methodology; Formal analysis; Writing – review and editing. Manoj Kumar S: Writing – original draft; Writing – review and editing.

REFERENCES

1. Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies*, *58*(2), 277–297. https://doi.org/10.2307/2297968
2. Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics*, *68*(1), 29–51. https://doi.org/10.1016/0304-4076(94)01642-D
3. Athanasoglou, P. P., Brissimis, S. N., & Delis, M. D. (2008). Bank-specific, industry-specific and macroeconomic determinants of bank profitability. *Journal of International Financial Markets, Institutions and Money*, *18*(2), 121–136. https://doi.org/10.1016/j.intfin.2006.07.001
4. Berger, A. N. (1995). The relationship between capital and earnings in banking. *Journal of Money, Credit and Banking*, *27*(2), 432–456.
5. Berger, A. N., Bonime, S. D., Covitz, D. M., & Hancock, D. (2000). Why are bank profits so persistent? The roles of product market competition, informational opacity, and regional/macroeconomic shocks. *Journal of Banking & Finance*, *24*(7), 1203–1235. https://doi.org/10.1016/S0378-4266(99)00124-7
6. Berger, A. N., & Bouwman, C. H. S. (2009). Bank liquidity creation. *Review of Financial Studies*, *22*(9), 3779–3837. https://doi.org/10.1093/rfs/hhn104
7. Berger, A. N., & DeYoung, R. (1997). Problem loans and cost efficiency in commercial banks. *Journal of Banking & Finance*, *21*(6), 849–870. https://doi.org/10.1016/S0378-4266(97)00003-4
8. Bhattacharyya, A., Lovell, C. A. K., & Sahay, P. (1997). The impact of liberalization on the productive efficiency of Indian commercial banks. *European Journal of Operational Research*, *98*(2), 332–345.
9. Bhaumik, S. K., & Dimova, R. (2004). How important is ownership in a market with level playing field? The Indian banking sector revisited. *Journal of Comparative Economics*, *32*(1), 165–180.
10. Bhaumik, S. K., & Piesse, J. (2008). Does lending behaviour of banks in emerging economies vary by ownership? Evidence from the Indian banking sector. *Economic Systems*, *32*(2), 177–196. https://doi.org/10.1016/j.ecosys.2007.04.004
11. Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, *87*(1), 115–143. https://doi.org/10.1016/S0304-4076(98)00009-8
12. Bond, S. R. (2002). Dynamic panel data models: A guide to micro data methods and practice. *Portuguese Economic Journal*, *1*(2), 141–162. https://doi.org/10.1007/s10258-002-0009-9
13. Bourke, P. (1989). Concentration and other determinants of bank profitability in Europe, North America and Australia. *Journal of Banking & Finance*,

13(1), 65–79. https://doi.org/10.1016/0378-4266(89)90020-4

14. Cameron, A. C., Gelbach, J. B., & Miller, D. L. (2008). Bootstrap-based improvements for inference with clustered errors. *Review of Economics and Statistics*, *90*(3), 414–427. https://doi.org/10.1162/rest.90.3.414
15. Cameron, A. C., & Miller, D. L. (2015). A practitioner's guide to cluster-robust inference. *Journal of Human Resources*, *50*(2), 317–372. https://doi.org/10.3368/jhr.50.2.317
16. Demirgüç-Kunt, A., & Huizinga, H. (1999). Determinants of commercial bank interest margins and profitability: Some international evidence. *World Bank Economic Review*, *13*(2), 379–408. https://doi.org/10.1093/wber/13.2.379
17. Dietrich, A., & Wanzenried, G. (2011). Determinants of bank profitability before and during the crisis: Evidence from Switzerland. *Journal of International Financial Markets, Institutions and Money*, *21*(3), 307–327. https://doi.org/10.1016/j.intfin.2010.11.002
18. Driscoll, J. C., & Kraay, A. C. (1998). Consistent covariance matrix estimation with spatially dependent panel data. *Review of Economics and Statistics*, *80*(4), 549–560. https://doi.org/10.1162/003465398557825
19. Drukker, D. M. (2003). Testing for serial correlation in linear panel-data models. *The Stata Journal*, *3*(2), 168–177. https://doi.org/10.1177/1536867X0300300206
20. Dumitrescu, E.-I., & Hurlin, C. (2012). Testing for Granger non-causality in heterogeneous panels. *Economic Modelling*, *29*(4), 1450–1460. https://doi.org/10.1016/j.econmod.2012.02.014
21. Everaert, G., & Pozzi, L. (2007). Bootstrap-based bias correction for dynamic panels. *Journal of Economic Dynamics and Control*, *31*(4), 1160–1184. https://doi.org/10.1016/j.jedc.2006.04.005
22. Goddard, J., Molyneux, P., & Wilson, J. O. S. (2004). The profitability of European banks: A cross-sectional and dynamic panel analysis. *The Manchester School*, *72*(3), 363–381. https://doi.org/10.1111/j.1467-9957.2004.00397.x
23. Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica*, *50*(4), 1029–1054. https://doi.org/10.2307/1912775
24. Hausman, J. A. (1978). Specification tests in econometrics. *Econometrica*, *46*(6), 1251–1271. https://doi.org/10.2307/1913827
25. Ho, T. S. Y., & Saunders, A. (1981). The determinants of bank interest margins: Theory and empirical evidence. *Journal of Financial and Quantitative Analysis*, *16*(4), 581–600. https://doi.org/10.2307/2330377
26. Hoechle, D. (2007). Robust standard errors for panel regressions with cross-sectional dependence. *The Stata Journal*, *7*(3), 281–312. https://doi.org/10.1177/1536867X0700700301
27. Judson, R. A., & Owen, A. L. (1999). Estimating dynamic panel data models: A guide for macroeconomists. *Economics Letters*, *65*(1), 9–15. https://doi.org/10.1016/S0165-1765(99)00130-5
28. Keeley, M. C. (1990). Deposit insurance, risk, and market power in banking. *American Economic Review*, *80*(5), 1183–1200.
29. Kiviet, J. F. (1995). On bias, inconsistency, and efficiency of various estimators in dynamic panel data models. *Journal of Econometrics*, *68*(1), 53–78. https://doi.org/10.1016/0304-4076(94)01643-E
30. Kumbhakar, S. C., & Sarkar, S. (2003). Deregulation, ownership, and productivity growth in the banking industry: Evidence from India. *Journal of Money, Credit and Banking*, *35*(3), 403–424.
31. Louzis, D. P., Vouldis, A. T., & Metaxas, V. L. (2012). Macroeconomic and bank-specific determinants of non-performing loans in Greece: A comparative study of mortgage, business and consumer loan portfolios. *Journal of Banking & Finance*, *36*(4), 1012–1027. https://doi.org/10.1016/j.jbankfin.2011.10.012
32. Maddala, G. S., & Wu, S. (1999). A comparative study of unit root tests with panel data and a new simple test. *Oxford Bulletin of Economics and Statistics*, *61*(S1), 631–652. https://doi.org/10.1111/1468-0084.0610s1631
33. Molyneux, P., & Thornton, J. (1992). Determinants of European bank profitability: A note. *Journal of Banking & Finance*, *16*(6), 1173–1178. https://doi.org/10.1016/0378-4266(92)90065-8
34. Mundlak, Y. (1978). On the pooling of time series and cross section data. *Econometrica*, *46*(1), 69–85. https://doi.org/10.2307/1913646
35. Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica*, *49*(6), 1417–1426. https://doi.org/10.2307/1911408
36. Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics*, *22*(2), 265–312. https://doi.org/10.1002/jae.951
37. Pesaran, M. H. (2021). General diagnostic tests for cross-sectional dependence in panels. *Empirical Economics*, *60*(1), 13–50. https://doi.org/10.1007/s00181-020-01875-7
38. Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies*, *22*(1), 435–480. https://doi.org/10.1093/rfs/hhn053
39. Podpiera, J., & Weill, L. (2008). Bad luck or bad management? Emerging banking market experience. *Journal of Financial Stability*, *4*(2), 135–148. https://doi.org/10.1016/j.jfs.2008.01.005
40. Reserve Bank of India. (2005–2025). *Select ratios of scheduled commercial banks* [Data set]. Reserve Bank of India. https://data.rbi.org.in
41. Roodman, D. (2009a). How to do xtabond2: An introduction to difference and system GMM in Stata. *The Stata Journal*, *9*(1), 86–136. https://doi.org/10.1177/1536867X0900900106
42. Roodman, D. (2009b). A note on the theme of too many instruments. *Oxford Bulletin of Economics and Statistics*, *71*(1), 135–158. https://doi.org/10.1111/j.1468-0084.2008.00542.x
43. Sarkar, J., Sarkar, S., & Bhaumik, S. K. (1998). Does ownership always matter? Evidence from the Indian

banking industry. *Journal of Comparative Economics, 26*(2), 262–281.

44. Sensarma, R. (2006). Are foreign banks always the best? Comparison of state-owned, private and foreign banks in India. *Economic Modelling, 23*(4), 717–735. https://doi.org/10.1016/j.econmod.2006.04.002
45. Short, B. K. (1979). The relation between commercial bank profit rates and banking concentration in Canada, Western Europe, and Japan. *Journal of Banking & Finance, 3*(3), 209–219.
46. Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step GMM estimators. *Journal of Econometrics, 126*(1), 25–51. https://doi.org/10.1016/j.jeconom.2004.02.005