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When Growth Changes the Risk-Profitability Transmission A study on Indian public sector banks

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Abstract: This study investigates how asset deployment, credit risk and operating efficiency combine to shape shareholder profitability in Indian public sector banks, and whether the structural relationships vary across GDP-growth regimes.

The archived dataset comprises 100 bank-year observations from ten listed Indian public sector banks. A variance-based path model was estimated in SmartPLS using 6,000 bootstrap resamples. The model connects advances-to-deposits (ADV/DEP), gross non-performing assets (GNPA), net interest margin (NIM), operating profit margin (OPM), return on assets (ROA) and return on equity (ROE). Predictive relevance, effect sizes and GDP-based multigroup comparisons were assessed.

ADV/DEP is negatively associated with GNPA ($\beta = -.629$, $p < .001$) and positively associated with NIM ($\beta = .466$, $p < .001$) and ROA ($\beta = .151$, $p = .001$). GNPA strongly reduces OPM ($\beta = -.825$, $p < .001$); OPM increases ROA ($\beta = .796$, $p < .001$), and ROA increases ROE ($\beta = 1.000$, $p < .001$). Although the direct GNPA $\rightarrow$ ROE path is not significant, the GNPA $\rightarrow$ OPM $\rightarrow$ ROA $\rightarrow$ ROE indirect effect is negative and significant ($\beta = -.710$, $p < .001$). The model explains 91.2% of ROE variance and reports SRMR = .018. GDP-group differences are significant for ADV/DEP $\rightarrow$ GNPA, GNPA $\rightarrow$ ROE, and NIM $\rightarrow$ GNPA, as well as two mediated ADV/DEP paths.

The paper moves beyond isolated profitability ratios by showing how credit risk reaches shareholder returns through an operating-efficiency chain and how that chain changes with macroeconomic conditions.

Keywords: Public sector banks, credit risk, profitability, non-performing assets, PLS-SEM, GDP, India.

1. Introduction

Public sector banks occupy a central position in India's credit allocation system, but their shareholder returns depend on more than the volume of lending. Expanding advances can improve interest income and asset utilisation, yet deterioration in loan quality raises provisioning and operating burdens. The empirical challenge is therefore to explain how balance-sheet deployment, credit risk and operating efficiency jointly transmit into return on equity.

Prior banking studies typically examine profitability determinants through accounting regressions or estimate efficiency through frontier methods. Both traditions are valuable, but a single-equation design may conceal the sequence through which an upstream balance-sheet decision changes downstream profitability. Problem-loan research, for example, links asset-quality deterioration to operating inefficiency *(Berger & DeYoung, 1997)*, while macro-financial research shows that banking fragility is sensitive to growth conditions *(Demirguc-Kunt & Detragiache, 1998)*.

This study integrates six observed financial ratios in a variance-based path model and tests both direct and mediated relationships. It then compares the model across two GDP-growth groups. The contribution is threefold. First, it represents bank performance as a transmission system rather than a list of independent determinants. Second, it distinguishes direct from total credit-risk effects on shareholder returns. Third, it shows that selected paths are GDP-contingent, giving bank managers and supervisors a regime-sensitive interpretation of risk and profitability.

2. Theory and hypotheses

2.1. Asset deployment, risk and margins

The advances-to-deposits ratio indicates how intensively a bank converts deposit funding into earning assets. Greater deployment may improve NIM and ROA if pricing and underwriting are adequate, but aggressive lending can also alter asset quality. The sign of the ADV/DEP-GNPA association is therefore an empirical matter. The archived model proposes direct paths from ADV/DEP to GNPA, NIM and ROA.

2.2. Credit risk and the operating-profitability channel

GNPA captures realised deterioration in the loan book. Higher GNPA can reduce operating profitability through foregone interest, recovery costs and provisioning. OPM should then affect ROA, which expresses profit relative to total assets. ROA, in turn, is an accounting bridge to shareholder profitability. This sequence implies that credit risk may influence ROE predominantly through mediation even when its direct path is weak.

2.3. Macroeconomic contingency

Borrower cash flows, credit demand and loan migration vary with aggregate growth. Consequently, the same balance-sheet configuration may yield different risk and profitability consequences in weaker and stronger GDP regimes. The study therefore tests whether structural paths and mediated effects differ between the two reported GDP groups.

H1a-c: ADV/DEP is associated with GNPA, NIM and ROA. H2a-b: GNPA is associated with OPM and ROE. H3a-c: NIM is associated with GNPA, ROA and ROE. H4: OPM is positively associated with ROA. H5: ROA is positively associated with ROE. H6a-e: the five specified indirect effects are significant. H7: selected structural relationships differ across GDP regimes.

3. Method

3.1. Design, sample and variables

The study uses archival annual financial-ratio data for ten Indian public sector banks listed on the Bombay Stock Exchange. The source reports 100 bank-year observations over a ten-year window described as 2010-2020. Because 2010-2020 inclusive contains eleven calendar years, the exact start/end convention should be verified against the raw panel before submission. ADV/DEP is the exogenous ratio; GNPA, NIM, OPM, ROA and ROE are endogenous observed variables. GDP growth is used to form two equal groups of 50 observations.

3.2. Estimation strategy

SmartPLS 3 was used to estimate the recursive path model with 6,000 bootstrap resamples. PLS-SEM is treated here as variance-based path analysis of observed financial ratios, not as a latent measurement model. Evaluation covers path coefficients, t statistics, p values, inner VIF, f2, R2, blindfolding Q2, SRMR and PLS multigroup analysis. Interpretation emphasises predictive associations because the observational panel and contemporaneous ratios do not, by themselves, identify causality.

4. Results

4.1. Structural model

Seven of the ten direct paths are significant. ADV/DEP has a large negative relationship with GNPA and a moderate positive relationship with NIM. GNPA has the strongest negative direct relationship in the model, reducing OPM. The profitability chain OPM->ROA->ROE is strongly positive. Direct GNPA->ROE, NIM->GNPA and NIM->ROE paths are not significant.

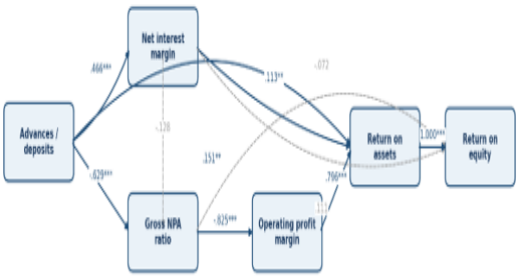

Figure 1: Reconstructed structural model with reported standardised path coefficients

Note. $^{**}p < .01$; $^{***}p < .001$. Grey dashed paths are not statistically significant. Values are reproduced from the archived thesis tables.

4.2. Mediation

All five specified indirect effects are significant. Most importantly, GNPA has no significant direct relationship with ROE, but has a strong negative sequential indirect effect through OPM and ROA. This pattern is consistent with indirect-only mediation: asset-quality deterioration reaches shareholders primarily by compressing operating profitability and asset returns.

All Q2 values exceed zero, indicating predictive relevance. The source reports SRMR=.018, below the conventional .08 guideline. Inner VIF values range from 1.00 to 4.078, below 5 but with two values above the more conservative threshold of 3. The largest reported f2 effects are OPM->ROA (3.647), ROA->ROE (3.239) and GNPA->OPM (2.132).

4.3. GDP-regime heterogeneity

The source divides the 100 observations into two equal groups using a reported operational cut-point of GDP growth at 7.04%. Five cross-group differences are significant. The ADV/DEP-GNPA relationship is more negative in the lower-growth group (-.814 versus -.476). NIM->GNPA is non-significant and positive below the cut-point (.103), but significant and negative above it (-.299). ADV/DEP->ROA and NIM->ROA are significant only in the higher-growth group.

Table 1: Direct-effect results

Hyp.	Path	β	t	p	Decision
H1.1	ADV/DEP → GNPA	−.629	10.252	< .001	Supported
H1.2	ADV/DEP → NIM	.466	7.984	< .001	Supported
H1.3	ADV/DEP → ROA	.151	3.462	.001	Supported
H2.1	GNPA → OPM	−.825	23.129	< .001	Supported
H2.2	GNPA → ROE	.111	.698	.485	Not supported
H3.1	NIM → GNPA	−.128	1.578	.115	Not supported
H3.2	NIM → ROA	.113	2.671	.008	Supported
H3.3	NIM → ROE	−.072	1.761	.078	Not supported
H4	OPM → ROA	.796	16.841	< .001	Supported
H5	ROA → ROE	1.000	7.774	< .001	Supported

Table 2: Bootstrapped indirect effects

Hyp.	Indirect path	β	t	p
H6a	ADV/DEP → GNPA → OPM	.519	9.454	< .001
H6b	ADV/DEP → GNPA → OPM → ROA → ROE	.446	5.073	< .001
H6c	GNPA → OPM → ROA	−.657	12.512	< .001
H6d	GNPA → OPM → ROA → ROE	−.710	6.217	< .001
H6e	OPM → ROA → ROE	.856	6.924	< .001

Table 3: Endogenous-construct performance

Outcome	R^2	Q^2	Interpretation
NIM	.217	.206	Moderate
GNPA	.487	.461	Moderate/high
OPM	.681	.298	High
ROA	.883	.401	Substantial
ROE	.912	.329	Substantial

Data-integrity note. The thesis also reports an overall mean GDP growth of 6.64% while calling 7.04% the average-based split. The raw grouping variable and cut-point must therefore be verified before journal submission. The paper retains 7.04% only as the operational threshold used in the archived MGA output.

5. Discussion

The findings reveal a layered risk-profitability architecture. Asset deployment is associated with lower reported GNPA and higher NIM and ROA, but its most consequential routes are indirect. GNPA reduces OPM sharply; OPM then raises ROA, which transmits into ROE. This mechanism reconciles the non-significant direct GNPA-ROE path with the significant negative total effect reported in the source. Credit risk is economically consequential because it changes the operating engine of profitability, not because a contemporaneous direct coefficient necessarily appears.

GDP-regime heterogeneity adds a macro-prudential interpretation. The stronger negative ADV/DEP-GNPA coefficient in the lower-growth group may reflect differences in the composition, recognition or denominator behaviour of bank ratios; it should not be read as proof that aggressive lending improves asset quality. Above the cut-point, NIM is negatively associated with GNPA and both ADV/DEP and NIM contribute to ROA. These differences suggest that margin generation and asset utilisation become more directly convertible into profitability in stronger growth conditions.

The very high ROA-ROE coefficient and ROE R2 warrant caution. Because ROA and ROE share net income in their numerators, mechanical overlap can inflate associations. A Q1-level revision should test lagged specifications, bank and year effects, alternative profitability measures, and endogeneity-robust estimators alongside the PLS path model.

6. Implications

6.1. Managerial implications

Bank managers should treat GNPA reduction as an operating-profitability intervention, not only a compliance target. Early-warning systems, recovery efficiency and provisioning discipline can protect OPM and ROA before shareholder returns deteriorate. The significant ADV/DEP-NIM and ADV/DEP-ROA paths imply that credit deployment remains productive, but the benefit depends on underwriting quality. Regime-sensitive stress dashboards should therefore connect loan growth, GNPA migration, margin compression and ROA rather than monitoring each ratio independently.

6.2. Policy and investor implications

Supervisors can use the mediated chain to design stress scenarios in which asset-quality shocks propagate through operating profitability to capital-market outcomes. Investors should avoid interpreting a non-significant contemporaneous GNPA-ROE coefficient as evidence that credit risk is immaterial; the indirect effect is both statistically strong and economically coherent. GDP-state comparisons also support conditional, rather than constant-parameter, forecasts.

7. Limitations and future research

The analysis has four major limitations. First, 100 observations and ten banks constrain external validity. Second, the source's year-window and GDP cut-point descriptions are internally inconsistent and require raw-data verification. Third, contemporaneous observational ratios cannot establish causal effects, despite the causal language used in the thesis. Fourth, several variables share accounting components, potentially producing mechanical correlation; the coefficient of 1.000 for ROA->ROE is a warning sign.

Future research should reconstruct the panel from audited bank statements and RBI databases, report the bank list and missing-data rules, winsorise extreme ratios, and estimate dynamic panel or system-GMM robustness models. Lagged GNPA, macro controls, bank fixed effects, capital adequacy, size and ownership reforms should be incorporated. For the multigroup analysis, measurement invariance is not relevant to single observed ratios, but permutation-based coefficient comparisons and continuous GDP interactions would avoid information loss from dichotomisation.

8. Conclusion

Indian public sector bank profitability emerges from a transmission chain: balance-sheet deployment affects credit risk and margins; credit risk reshapes operating profitability; operating profitability determines ROA; and ROA transmits into ROE. GDP conditions alter several links in that chain. The study's most durable insight is therefore not a single coefficient, but the distinction between direct and mediated risk effects.

References

1. 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
2. Creel, J., Hubert, P., & Labondance, F. (2015). Financial stability and economic performance. Economic Modelling, 48, 25–40. https://doi.org/10.1016/j.econmod.2014.10.025
3. Demirgüç-Kunt, A., & Detragiache, E. (1998). The determinants of banking crises in developing and developed countries. IMF Staff Papers, 45(1), 81–109. https://doi.org/10.2307/3867571
4. Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). A primer on partial least squares structural equation modeling (PLS-SEM) (2nd ed.). Sage.
5. Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. European Business Review, 31(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203
6. Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. Advances in International Marketing, 20, 277–319. https://doi.org/10.1108/S1474-7979(2009)0000020014
7. Kock, N., & Hadaya, P. (2018). Minimum sample size estimation in PLS-SEM: The inverse square root and gamma-exponential methods. Information Systems Journal, 28(1), 227–261. https://doi.org/10.1111/isj.12131
8. Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. Behavior Research Methods, 40(3), 879–891. https://doi.org/10.3758/BRM.40.3.879
9. Reserve Bank of India. (2021). Report on trend and progress of banking in India 2020-21.
10. Ringle, C. M., Wende, S., & Becker, J.-M. (2015). SmartPLS 3 [Computer software]. SmartPLS GmbH.
11. Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J.-H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict. European Journal of Marketing, 53(11), 2322–2347. https://doi.org/10.1108/EJM-02-2019-0189
12. Wonglimpiyarat, J. (2014). Competition and challenges of mobile banking: A systematic review of major bank models in the Thai banking industry. The Journal of High Technology Management Research, 25(2), 123–131. https://doi.org/10.1016/j.hitech.2014.07.005