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Deleveraging and Bank Resilience: Does Asset Quality Stress Constrain Credit Growth?

Evidence from India's Scheduled Commercial Banks

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Abstract

This study examines whether stress in bank loan portfolios constrains subsequent credit growth in India's Scheduled Commercial Banks (SCBs) and how far the banking sector's balance-sheet repair has translated into resilience. Using annual data from 1996–97 to 2024–25, it estimates an Autoregressive Distributed Lag (ARDL) model in which annual growth in gross advances depends on its own lag and the previous year's growth in gross NPAs. The model explains about 61.7 percent of the variation in credit growth. Credit growth is highly persistent (coefficient 0.71, significant at the 1 percent level), whereas lagged gross NPA growth has the expected negative sign but is statistically insignificant (coefficient -0.063 , $p = 0.136$); a robustness check using net NPA growth gives the same conclusion. Descriptive evidence from the 2015–18 clean-up shows a sharp slowdown in lending after the jump in NPAs, suggesting that any credit constraint operates mainly in severe-stress episodes. Banking indicators for 2014–2024 show a near-tripling of credit, a fourfold rise in net profit, a fall in the gross NPA ratio from 8.3 to 2.8 percent between 2020 and 2024, and a rise in provision coverage from 44.7 to 76.4 percent. The findings show that credit dynamics are driven more by momentum and broader factors than by asset-quality stress alone, and that sustained resilience requires continued vigilance.

Keywords: Credit Growth; Non-Performing Assets; ARDL Model; Banking Sector Resilience; Deleveraging; Scheduled Commercial Banks; India

JEL Classification: G21, C32, E51, G01

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1. Introduction

Banks accumulate bad loans; their effects extend well beyond the banking sector. Provisions erode profits and capital, lenders become cautious, and borrowers who depend on bank credit, including smaller firms and non-bank financial companies, find funding harder to obtain. The Indian experience after 2015 illustrates this concern. The Reserve Bank of India's Asset Quality Review (AQR) brought long-hidden stress to light, and fresh lending slowed as banks cleaned up their balance sheets. Studies observe that bank clean-ups can reduce credit supply unless capital is replenished in time (Chopra, Subramanian and Tantri, 2021).

The banking sector has since moved from stress to strength. By March 2025, the system's balance sheet had expanded by 11.2 percent, the gross NPA ratio had fallen to 2.2 percent, and the average capital-to-risk-weighted-assets ratio (CRAR) was 17.4 percent, with all banks meeting regulatory requirements (Reserve Bank of India, 2025b). The RBI's Financial Stability Report of June 2026 places the gross NPA ratio at a historic low of 1.8 percent as of March 2026 (Reserve Bank of India, 2026). The policy question is whether this balance-sheet deleveraging provides a stable platform for credit growth, and whether earlier stress actually held lending back.

This article examines how much one year's growth in gross NPAs predicts the next year's credit growth, after accounting for the strong persistence of credit growth. It also reviews key banking indicators for 2014–2024 to assess resilience. The study provides an annual, system-wide estimate of the relationship between lagged NPA growth and credit growth over almost three decades. It reports a robustness check with net NPAs. It places the estimates alongside descriptive evidence on episodes of stress and recovery.

2. Literature and Hypothesis

The available literature argues that losses and low capital reduce banks' willingness or ability to lend. The 'credit crunch' literature documented how capital constraints reduced lending in the early 1990s United States (Bernanke and Lown, 1991), and also showed that bank balance-sheet strength shapes how monetary policy and shocks pass through to credit supply (Kashyap and Stein, 2000).

Credit expansion leads to losses, with problems emerging only after a lag (Keeton, 1999). Banks that have experienced loan losses become more conservative, a pattern linked to institutional memory in lending behaviour (Berger and Udell, 2004). Studies of non-performing loans also stress their dependence on macroeconomic and bank-specific factors, such as GDP growth, interest rates and bank efficiency (Louzis, Vouldis and Metaxas, 2012).

Capital-constrained banks may instead delay recognising losses and keep lending to impaired borrowers, misallocating credit and crowding out healthy firms (Peek and Rosengren, 2005; Caballero, Hoshi and Kashyap, 2008).

These literatures imply competing effects. A cautious-bank or capital-constraint channel predicts a negative association between past NPA growth and credit growth, while forbearance and rollover predict a weak or absent association in the short run. Another factor is strong credit momentum: lending in one year tends to carry into the next through existing commitments and multi-year projects.

The hypothesis tested is therefore: Higher gross NPA growth in the previous year is associated with lower credit growth in the current year, after controlling for lagged credit growth.

3. Data and Methodology

3.1 Data

Annual data for all Scheduled Commercial Banks cover 1996–97 to 2024–25, drawn from bank annual reports and RBI publications. Credit growth is the annual percentage growth of gross advances. Gross NPA growth is the annual percentage growth of gross NPAs; net NPA growth is used as a robustness variable. Data from 2023–24 include the effect of the merger of a non-bank with a bank effective 1 July 2023, which raises measured advances and deposits in that year. Key banking indicators for 2014–2024 (credit, deposits, profit, capital, asset quality, provisioning, returns and margins) are taken from the RBI.

3.2 Why an ARDL-type specification

A sudden surge in NPAs does not stop fresh lending overnight, as banks gradually adjust provisions, rebuild capital buffers, and tighten lending criteria, and credit growth carries momentum from existing commitments. The Autoregressive Distributed Lag framework, which includes lags of both the dependent and explanatory variables, is designed for these dynamics (Pesaran and Shin, 1999; Pesaran, Shin and Smith, 2001). Using growth rates rather than levels also limits the spurious trends common in raw financial data.

The estimated model includes one lag of credit growth and one lag of gross NPA growth:

$$CG(t) = \beta_0 + \beta_1 \Delta GNPA(t-1) + \beta_2 CG(t-1) + \varepsilon(t)$$

Where:

$CG(t)$ is the annual growth rate of gross advances,

$\Delta GNPA(t-1)$ is the previous year's growth rate of gross NPAs and

$CG(t-1)$ is the previous year's credit growth.

The coefficient β_1 tests H1 (expected sign negative), and β_2 captures persistence. Because the model includes a lagged dependent variable, the implied long-run effect of a permanent change in NPA growth is $\beta_1 \div (1 - \beta_2)$, and the speed of adjustment depends on β_2 . Both are reported below.

3.3 Diagnostics

The model is estimated using ordinary least squares. Overall fit is judged by R^2 , adjusted R^2 and the F-statistic. Serial correlation is assessed with the Durbin–Watson statistic (Durbin and Watson, 1950), which is biased towards 2 when a lagged dependent variable is included; the Breusch–Godfrey test (Breusch, 1978; Godfrey, 1978) is therefore the more appropriate check, and stationarity of the growth series should be confirmed with unit-root tests (Dickey and Fuller, 1979). [Insert unit-root and Breusch–Godfrey results from the estimation output.]

4. Descriptive Evidence: Credit Growth after Asset-Quality Shocks

Table 1 compares annual credit growth with the previous year's gross NPA growth for the clean-up and recovery years.

Table 1: Credit growth and lagged gross NPA growth, 2015–16 to 2024–25 (% year-on-year)

Year	Credit growth, t	Gross NPA growth, t–1
2015–16	8.2	22.8
2016–17	3.6	89.4
2017–18	9.4	29.2
2018–19	11.0	31.1
2019–20	6.1	–9.9
2020–21	4.4	–4.0
2021–22	11.9	–6.8
2022–23	15.8	–11.1
2023–24	18.6	–23.0
2024–25	11.1	–15.9

Source: Computed from loan-asset classification data of SCBs (total advances and gross NPAs), annual reports of banks and RBI publications. 2023–24 credit growth is raised by a merger effective 1 July 2023.

Table 1 shows that gross NPAs increased in 2015–16 (up 89.4 percent), credit growth fell to 3.6 percent in 2016–17, the lowest of any year shown, which fits the idea that a severe recognition shock restrains lending. Yet credit growth recovered to 11.0 percent in 2018–19 even though gross NPAs had grown 31.1 percent the year before, so the relationship is not stable. Credit growth was low in 2019–20 and 2020–21 despite falling NPAs, a period dominated by the pandemic and a slowdown in demand. From 2021–22 onwards, credit growth strengthened as NPAs fell.

5. Results

5.1 Main specification (gross NPAs)

Table 2: ARDL-type estimates, dependent variable: credit growth, t

Variable	Coefficient	p-value	Interpretation
Constant	[insert]	[insert]	–
Gross NPA growth, t–1	–0.0634	0.136	Negative, not significant at 5%
Credit growth, t–1	0.7122	<0.001	Significant, high persistence
R ² / adjusted R ²	0.617 / 0.585		61.7% of variation explained
F-statistic	19.35	<0.001	Model significant overall
Durbin–Watson	1.79		No serious first-order autocorrelation evident
Observations	27		

Note: OLS estimates using annual data, 1996–97 to 2024–25, with one lag each of the dependent and explanatory variables.

The model explains about 61.7 percent of the variation in annual credit growth. The coefficient on lagged gross NPA growth is –0.0634: a one percentage point increase in gross

NPA growth in the previous year is associated with a 0.06 percentage point reduction in credit growth. The p-value of 0.136 means that the relationship is not significant at the 5 percent level, and the data therefore do not provide sufficient statistical evidence to accept H1. The negative sign is consistent with banks becoming more cautious when asset-quality pressure builds, but this should be read as an association rather than a causal effect.

The coefficient on lagged credit growth is 0.7122 and highly significant, indicating strong persistence in credit growth: higher lending in one year tends to be followed by strong lending in the next, all else equal. The implications are that a shock to credit growth fades slowly, with a half-life of about two years, and the implied long-run effect of a sustained increase in NPA growth is $-0.0634 \div (1 - 0.7122) \approx -0.22$, meaning that a permanent 10 percentage point rise in NPA growth would lower steady-state credit growth by about 2.2 percentage points.

5.2 Robustness: net NPA growth

The model was also estimated with net NPA growth in place of gross NPA growth.

Table 3: Robustness check – lagged net NPA growth

Variable	Coefficient	p-value	Interpretation
Constant	3.523	0.135	Not significant
Net NPA growth, t-1	-0.00857	0.114	Negative, not significant
Credit growth, t-1	0.7937	<0.001	Significant
R ² / adjusted R ²	0.6216 / 0.5901		
F-statistic	19.71	<0.001	Model significant overall
Durbin–Watson	1.63		Some positive autocorrelation may remain

The estimated equation is $CG(t) = 3.523 - 0.00857 \Delta NPA(t-1) + 0.7937 CG(t-1)$. Persistence is large and significant; the NPA coefficient is negative but insignificant, and the fit is similar. The lower Durbin–Watson value of 1.63 suggests some positive autocorrelation may remain, reinforcing the need for caution with a sample of only 27 observations.

5.3 Why might the effect be weak?

Several explanations fit the findings: First, aggregation: system-wide series blend public sector banks, which faced the greatest stress, with private banks that largely maintained lending. Second, offsetting policy: recapitalisation and resolution mechanisms may have allowed lending to continue despite stress (Chopra et al., 2021). Third, forbearance and rollover before 2015 may have kept measured credit growing while NPAs built up unseen (Chari et al., 2021). Fourth, omitted variables: demand conditions, interest rates, capital adequacy, deposit growth and one-off events such as the pandemic and the 2023 merger also drive credit. Fifth, non-linearity: the constraint binds only in severe episodes, such as 2015–18, rather than uniformly across 27 years. Finally, the small sample reduces power, so a real but modest effect could fail to reach significance.

6. Resilience: Key Banking Indicators, 2014–2024

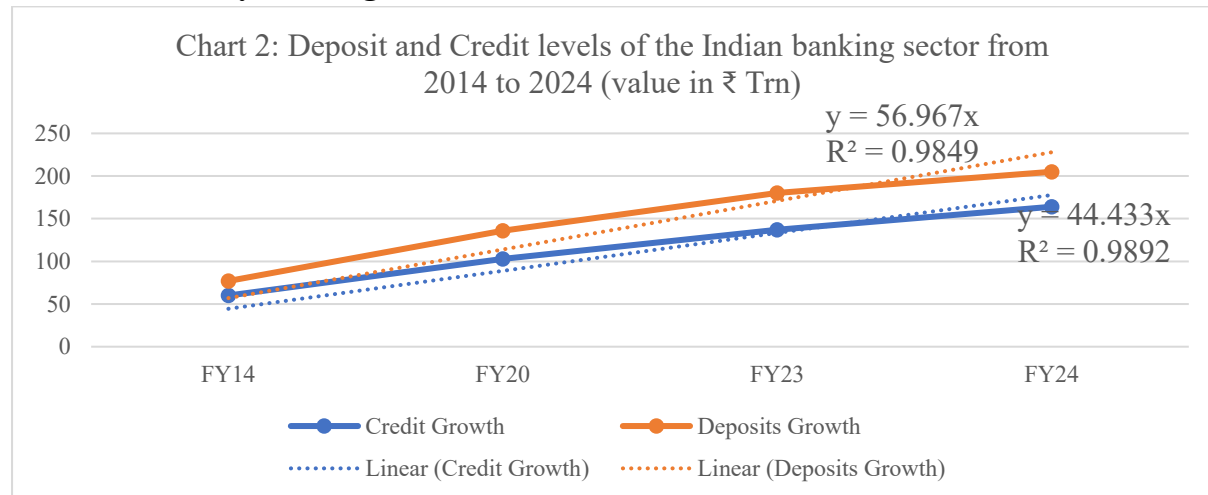


Chart 2 shows deposit and credit levels in the Indian banking sector from 2014 to 2024, highlighting the resilience of key banking indicators. Asset quality also improved over the period. The GNPA ratio fell from 8.3 percent in 2020 to 2.8 percent in 2024, while NNPA declined to just 0.6 percent. The PCR rose to 76.4 percent, indicating banks built stronger provisions against stressed assets. Capital adequacy remained comfortable, with CRAR at 16.8 per cent in 2024. The improvement in the Provision Coverage Ratio (PCR) reinforces this trend. PCR increased from 44.7 per cent in 2014 to 76.4 per cent in 2024, indicating that banks built substantially larger provisions against their gross NPAs and strengthened their ability to absorb losses from stressed loans during the period.

Table 4 summarises the improvement in overall banking health.

Table 4: Key banking indicators, FY14–FY24

Parameter	FY14	FY20	FY23	FY24	FY24 over FY14
Credit (₹ lakh crore)	60	103	137	164	2.7x
Credit growth (YoY, %)	13.9	6.1	15.0	20.2	
Deposits (₹ lakh core)	77	136	180	205	2.7x
Deposit growth (YoY, %)	14.1	7.9	9.6	13.5	
Net profit (₹ crores)	809	109	2,632	3,206	4.0x
CRAR (%)	13.0	14.8	17.1	16.8	—
GNPA ratio (%)	3.8	8.3	3.8	2.8	
NNPA ratio (%)	2.1	2.9	1.0	0.6	
PCR (%)	44.7	66.2	74.0	76.4	
Return on assets (%)	0.8	0.1	1.1	1.3	
Return on equity (%)	9.5	1.2	12.3	13.8	
Net interest margin (%)	2.7	2.9	3.7	3.6	

Source: RBI; SBI Research. Ratios may differ slightly from those in the companion article because of differences in source and coverage. FY24 growth is raised by the 2023 merger.

Table 2 shows that credit and deposits each rose about 2.7 times between FY14 and FY24, from ₹60 trillion to ₹164 trillion and from ₹77 trillion to ₹205 trillion. The credit-to-deposit ratio rose from about 78 percent to about 80 percent, which indicates that lending kept pace with funding without becoming heavily dependent on non-deposit sources. The very high FY24 credit growth of 20.2 percent should be read with care because of the merger effect noted

above. Net profit increased from ₹809 billion to ₹3,206 billion, with a low of ₹109 billion in FY20, when return on assets was only 0.1 per cent. By FY24 return on assets was 1.3 percent and return on equity 13.8 percent. Net interest margin jumped from 2.7 percent to 3.6 percent, peaking at 3.7 percent in FY23, which reflects higher income relative to interest costs together with lower provisioning needs. The gross NPA ratio fell from its FY20 level of 8.3 percent to 2.8 percent in FY24, and the net NPA ratio to 0.6 percent. Provision coverage climbed from 44.7 to 76.4 percent, which means that banks now hold substantial buffers against the NPAs that remain. Capital adequacy was comfortable, with CRAR at 16.8 percent, well above regulatory minima.

The data show that the post-AQR clean-up was not achieved at the expense of lending: credit grew strongly while NPAs fell. This is consistent with the regression result that asset-quality stress is only one of several influences on credit. Deleveraging of bank balance sheets, supported by recapitalisation, provisioning, and faster resolution, appears to have restored lending capacity. However, the cross-sectional composition of recent credit growth deserves attention: demand from retail and services borrowers has grown faster than deposits (Reserve Bank of India, 2025b), and fast-growing segments may be where risks build up unnoticed.

7. Limitations and Policy Implications

The analysis uses aggregate annual data, so power is limited, and the estimates are sensitive to specification. The model includes only one explanatory variable besides the lag and omits demand-side and macroeconomic controls. Regime shifts – the AQR, the introduction of the IBC, the pandemic and the 2023 merger – are not modelled. Aggregation hides differences between public and private banks. The results describe association, not causation.

Natural extensions include adding GDP growth, policy-rate and capital-adequacy controls; estimating a panel model by bank group or individual bank; including dummies for the 2015–18 clean-up and the pandemic; testing parameter stability with recursive methods such as CUSUM; and allowing for a non-linear or threshold effect of NPA growth.

The policy implications: First, because credit growth is highly persistent, lending decisions made during booms have lasting consequences, and stress may emerge only after a lag, which argues for supervisory attention to underwriting standards during periods of rapid expansion. Second, because the lending constraint binds most clearly in severe episodes, timely recapitalisation is needed to prevent clean-ups from causing credit contractions (Chopra et al., 2021). Third, early recognition of stress through transparent asset classification limits the scope for forbearance-driven misallocation of credit (Chari et al., 2021). Fourth, banks should maintain high provisioning and capital buffers through the cycle, since they allowed lending to recover while asset quality was repaired.

8. Conclusion

This study examined whether asset-quality stress constrains subsequent credit growth in Indian Scheduled Commercial Banks and how far balance-sheet repair has translated into resilience. An ARDL-type model explains about 61.7 percent of the variation in annual credit growth. Credit growth is highly persistent, with a coefficient of about 0.71, while lagged gross NPA growth has a negative but statistically insignificant effect (-0.063 , $p = 0.136$); a

robustness check with net NPAs gives the same result. Descriptive evidence suggests the constraint is visible mainly in the sharp 2016–17 slowdown following the AQR, rather than as a stable relationship across the full sample. The banking sector had larger, more profitable balance sheets, lower NPAs, stronger capital, and much higher provisioning. Credit expansion and balance-sheet repair occurred together, supported by recognition, recapitalisation, and resolution. Sustaining these gains requires prudent lending standards, monitoring emerging stress, adequate capital and provisioning, and timely resolution of problem assets, since rapid credit growth can create risks that emerge only after a considerable time.

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