

Regulatory Capital Buffers and Bank Resilience in India: Antifragility Evidence from Indian Scheduled Commercial Banks, 2016–2025

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Abstract

This study examines whether Basel III capital buffers serve as antifragility mechanisms, enabling banks to enhance stability in response to shocks rather than merely withstand them. A balanced panel of ten scheduled commercial banks (five public sector and five private sector) is analyzed over FY 2016–2025, encompassing three non-linear shock episodes: the IL&FS credit crisis (2018), the COVID-19 pandemic (2020–21), and the post-pandemic NPA resolution cycle. Financial stability is assessed using the Z-score. Three specifications are estimated: capital levels, excess buffers above regulatory minima, and year-on-year capital changes (Δ CRAR). CRAR, or Capital-to-Risk-Weighted-Assets Ratio, measures a bank's capital adequacy. In the capital levels and excess-buffer specifications, the $\text{CRAR} \times \text{Shock}$ interaction is not significant, suggesting that pre-existing buffer stocks do not provide increased protection during shocks. In contrast, the change specification reveals a significant $\Delta\text{CRAR} \times \text{Shock}$ interaction ($\beta = 21.55$, $p = 0.001$), indicating that banks increasing capital during shock periods are associated with substantially higher stability. This finding aligns with, but does not definitively establish, a causal antifragility mechanism. The principal implication is that Basel III fosters antifragility through a dynamic channel—the regulatory incentive to rebuild buffers under stress—rather than through passive buffer absorption. The Capital Conservation Buffer, which mandates capital rebuilding during stress, emerges as the framework's most consequential stability mechanism.

Keywords: Basel III, Antifragility, Bank Stability, Z-Score, Non-Linear Shocks

1. Introduction

The concept of antifragility, as introduced by Taleb (2012), refers to systems that benefit from disorder. In the context of banking regulation, a key question is whether Basel III's capital and liquidity buffers provide mere robustness—enabling banks to survive shocks without improvement—or genuine antifragility, whereby banks gain strength through exposure to shocks. This distinction is significant: if buffers are only robust, their optimal calibration serves as a minimum threshold to prevent failure. If they are antifragile, the process of building and rebuilding buffers generates stability gains that surpass the static benefit of simply maintaining them (Taleb & Douady, 2013).

The Indian banking sector offers a particularly instructive context for evaluating this proposition, having experienced a series of non-linear, accelerated, and interconnected shocks over the past decade. The IL&FS default of September 2018, which triggered cascading credit

stress across non-banking financial companies; the COVID-19 pandemic of 2020–21, an exogenous macroeconomic contraction accompanied by regulatory forbearance (RBI, 2021); and the post-pandemic NPA resolution cycle, during which banks recognized and wrote off accumulated stressed assets. Throughout this period, Basel III requirements were progressively tightened, with the full framework — including the complete Capital Conservation Buffer — becoming effective from October 2021 (BCBS, 2011; RBI, 2020).

The structural heterogeneity of the banking system enhances the analytical framework. Public sector banks (PSBs), which hold approximately 60 percent of system assets, entered the Basel III era with significant legacy non-performing assets and limited capital reserves. The Government's recapitalization programme (₹3.1 lakh crore, 2017–2021) necessitated both capital rebuilding and asset-quality recognition, exemplifying the stress-induced overcompensation that Taleb identifies as the mechanism of antifragility. In contrast, private sector banks maintained substantial capital surpluses and had minimal need to construct stress-driven buffers (Berger & Bouwman, 2013). These observations are contextualized within the NAVI framework—Non-linear, Accelerated, Volatile, Interconnected—which characterizes the current geopolitical and economic environment affecting banking systems.

This study offers three primary contributions. First, it empirically distinguishes between static antifragility—whether pre-existing buffer levels become more protective during shocks—and dynamic antifragility, which assesses whether buffer-building during shocks yields stability gains. Second, it evaluates three complementary specifications: capital levels, excess buffers above time-varying regulatory minima, and year-on-year capital changes, to identify the operative channel. Third, the findings demonstrate that the dynamic channel is significant, whereas the static channel is not, providing early empirical evidence consistent with Taleb's hormesis mechanism within banking regulation.

2. Review of Literature

2.1 Antifragility, Hormesis, and Overcompensation

Taleb (2012) grounds antifragility in the biological principle of hormesis: organisms exposed to moderate stressors overcompensate, building capacity exceeding the pre-stress baseline. Taleb and Douady (2013) formalise this mathematically, defining antifragility as a positive sensitivity of a system's payoff function to the volatility of the stressor variable. Applied to banking, the hormesis mechanism implies that the experience of a shock — and the regulatory requirement to rebuild capital afterwards — may produce stability gains unavailable to banks that were never stressed. This is distinct from mere resilience, which implies survival without improvement (Haldane & May, 2011).

2.2 Basel III Buffers and Bank Stability

The Z-score — $(ROA + Equity/Assets) / \sigma(ROA)$ — is the standard measure of bank stability (Laeven & Levine, 2009). Berger and Bouwman (2013) demonstrate that higher capital improves the probability of bank survival during crises and enhances market share for small banks, establishing the capital-stability channel that Basel III's buffer architecture seeks to activate. Demirgüç-Kunt and Huizinga (2010) find that banks' activity and funding strategies affect both risk and return, with implications for optimal capital structure. For India, Jaiwani and Gopalkrishnan (2023) document that Basel III regulations boost profitability and resilience for PSBs but have no comparable effect on private banks, thereby establishing the ownership-heterogeneity dimension central to the present study. Mir and Shah (2022), in a comparison of public and private sector banks in India, find that capital adequacy significantly affects bank

performance, with the effect varying across ownership structures. Fath Mala and Jumano (2025) show that CAR does not effectively mitigate risk in under-capitalised banks, suggesting a threshold effect. Sidhu, Rastogi, Gupte, and Bhimavarapu (2022) report a non-linear (inverted-U) relationship between LCR¹ and bank performance, suggesting regime-dependent buffer effects. Van den End and Tabbæ (2012) demonstrate that liquid-asset buffers reduce the probability of fire-sale deleveraging during stress. Nachane and Ghosh (2002) examine the procyclicality of Indian bank capital, finding that banks tend to delay provisioning for bad loans, magnifying economic cycle impacts — a pattern Basel III's capital conservation buffer was designed to address.

Importantly, most existing studies focus on the static relationship between buffer levels and stability. Few, if any, investigate whether the process of buffer-building—the dynamic increase in capital—produces stability effects distinct from those associated with the capital stock.

2.3 Hypotheses

Drawing on this literature, four hypotheses are tested:

H1: PSBs and private banks differ significantly in financial stability. This follows from the structural heterogeneity documented by Jaiwani and Gopalkrishnan (2023) and from the capital-gap evidence in the RBI Financial Stability Reports.

H2: Higher capital and liquidity buffers are associated with greater Z-score stability. This follows from the capital-survival channel established by Berger and Bouwman (2013) and the LCR-stability evidence in Van den End and Tabbæ (2012).

H3: The capital-stability relationship strengthens during shock periods (the antifragility hypothesis), consistent with Taleb's (2012) hormesis mechanism. This is tested through both static (levels/excess) and dynamic (Δ CRAR) specifications.

H4: The capital-stability relationship is stronger for PSBs than for private banks, consistent with PSBs' proximity to the regulatory floor and their active capital-rebuilding trajectory (Jaiwani & Gopalkrishnan, 2023).

3. Research Methodology

3.1 Sample and Variables

Ten scheduled commercial banks (five PSBs and five private banks) are observed annually from FY 2015–16 to FY 2024–25, resulting in 100 observations (80 with valid Z-scores and 20 after differencing). Although limited in number, these ten banks collectively represent approximately 60 percent of the total assets of Indian scheduled commercial banks, comprising the five largest PSBs by asset size and the five largest private sector banks. This sample captures the systemically significant segment of both ownership groups, ensuring that the findings reflect the behavior of institutions that are individually and collectively material to financial stability. The dependent variable is the Z-score, winsorized² at the 1st and 99th percentiles. Consistent with standard literature (Laeven & Levine, 2009), the Z-score is

¹ LCR indicates the Liquidity Coverage Ratio, which ensures that an institution maintains an adequate stock of unencumbered high-quality liquid assets (HQLA) that can be converted into cash to meet its liquidity needs over a 30-calendar-day severe stress scenario.

² Bank of Baroda (FY 2020-21) produced a raw Z-score of 1,167 — a statistical outlier driven by an extremely small σ (ROA) denominator. Winsorisation clips all Z-scores at the 1st and 99th percentile of the sample distribution

employed as the primary stability measure. To account for time-varying risk during the FY 2016–2025 period, which encompasses fundamentally different regulatory and macroeconomic regimes, a three-year rolling window for $\sigma(\text{ROA})$ is used instead of the full-period standard deviation.

Three independent variable specifications capture the buffer effect: (a) CRAR levels (%), (b) CRAR excess over time-varying regulatory minima (CRAR minus the applicable minimum CRAR, including the phased CCB; BCBS, 2011; RBI, 2015), and (c) year-on-year change in CRAR ($\Delta\text{CRAR} = \text{CRAR}_t - \text{CRAR}_{t-1}$). Three shock-period dummies are coded: D_ILFS (the IL&FS credit crisis, FY 2018–19), D_COVID1 (the first COVID-19 pandemic year, FY 2020–21), and D_COVID2 (the post-pandemic NPA resolution year, FY 2021–22). Controls include Gross NPA ratio and bank size (log of total assets). Data are drawn from RBI DBIE, bank Pillar 3 disclosures, and annual reports.

3.2 Econometric Specification

Three fixed-effects panel regressions with bank-clustered standard errors are estimated. The antifragility test is the interaction between the capital variable and a combined shock dummy ($\text{D_SHOCK} = 1$ if D_ILFS or D_COVID1 or D_COVID2):

$$Z_{it} = \alpha_i + \beta_1 \cdot \text{CRAR} + \beta_2 \cdot \text{LCR} + \beta_3 \cdot \text{D_SHOCK} + \beta_4 \cdot (\text{CRAR} \times \text{D_SHOCK}) + \gamma \cdot \text{Controls} + \varepsilon_{it} \quad (1)$$

$$Z_{it} = \alpha_i + \beta_1 \cdot \text{CRAR_excess} + \beta_2 \cdot \text{LCR_excess} + \beta_3 \cdot \text{D_SHOCK} + \beta_4 \cdot (\text{CRAR_excess} \times \text{D_SHOCK}) + \gamma \cdot \text{Controls} + \varepsilon_{it} \quad (2)$$

$$Z_{it} = \alpha_i + \beta_1 \cdot \Delta\text{CRAR} + \beta_2 \cdot \Delta\text{LCR} + \beta_3 \cdot \text{D_SHOCK} + \beta_4 \cdot (\Delta\text{CRAR} \times \text{D_SHOCK}) + \gamma \cdot \text{Controls} + \varepsilon_{it} \quad (3)$$

where Z_{it} is the Z-score, α_i are bank fixed effects, Controls include GNPA³ and SIZE (log of total assets), and ε_{it} is the error term. In each specification, β_4 is the coefficient of interest: a significant, positive β_4 indicates antifragility.

4. Results and Analysis

4.1 Descriptive Statistics

Table 1: Descriptive Statistics (N=80)

Variable	PSB Mean	PSB SD	Pvt Mean	Pvt SD	Full Mean	Full SD	Welch's t	p-value	Verdict
CRAR (%)	14.23	2.01	18.38	3.19	16.30	3.37	-6.9708	0	H1 ✓
LCR (%)	137.55	23.12	122.31	13.32	129.93	20.26	3.6116	0.0006	H1 ✓
ROA (%)	0.29	0.70	1.59	0.68	0.94	0.95	-8.3939	0	H1 ✓
ROE (%)	0.72	17.04	11.75	5.06	6.23	13.67	-3.923	0.0003	
GNPA (%)	8.30	4.51	2.78	1.97	5.54	4.43	7.0872	0	H1 ✓

³ GNPA = Gross Non-Performing Assets.

Equity/Assets (%)	6.21	0.72	12.08	2.20	9.15	3.37	16.0449	0	H1 ✓
CRAR Excess (pp ⁴)	3.12	1.69	7.27	3.14	5.19	3.26	-7.364	0	
ΔCRAR (pp/yr)	0.53	1.08	0.32	3.80	0.42	2.78	0.3381	0.73684	
Z-Score (winsorised)	46.80	120.52	138.70	168.03	92.75	152.47	-2.8107	0.0064	H1 ✓

PSBs exhibit substantially lower mean Z-scores (46.80 vs 138.70, Welch's $t = -2.81$, $p = 0.006$), lower CRAR (14.23% vs. 18.38%), Lower ROA (0.29% vs. 1.59%), Lower E/A (6.21% vs. 12.08%) and higher LCR (137.55 % vs. 122.31%) as well as GNPA (8.30% vs. 2.78%) than private banks. PSBs hold smaller excess buffers (3.12 pp vs 7.27 pp) but show higher mean ΔCRAR (+0.53 pp vs +0.32 pp), consistent with the active capital-rebuilding trajectory. All six core study variables differ significantly ($p < 0.01$), supporting H1.

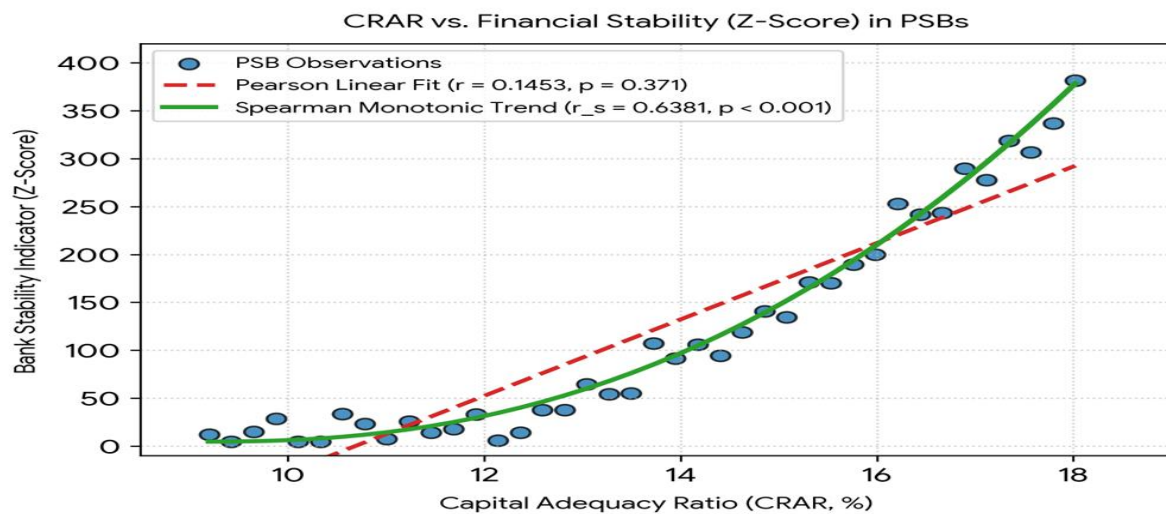
4.2 Correlation Analysis

Table 2: Correlation Analysis

Group	Variables	Pearson r	p	Spearman r_s	p	Interpretation
PSB	CRAR-Z	0.1453	0.3711	0.6381	0	Non-linear ★
PSB	CRARex-Z	0.1668	0.3035	0.5488	0.0002	Non-linear ★
PSB	LCR-Z	0.1964	0.2246	0.3038	0.0567	Marginal
Private	CRAR-Z	0.0574	0.725	0.2496	0.1203	Not significant
Private	CRARex-Z	0.0872	0.5925	0.2479	0.1231	Not significant
Private	LCR-Z	-0.0308	0.8504	0.0238	0.884	Not significant

⁴ **pp** denotes *percentage points*, used here to accurately represent absolute changes or differences in regulatory ratio values (such as ΔCRAR or regulatory cushions) rather than relative percentage growth.

Figure 1



A Pearson–Spearman divergence for PSBs (Pearson $r = 0.145$, $p = 0.371$; Spearman $r_s = 0.638$, $p < 0.001$) indicates a monotonic but non-linear CRAR–stability relationship. For private banks, both are insignificant ($r = 0.057$; $r_s = 0.250$).

4.3 Panel Regression

A methodological caveat must be considered before interpreting the regression results. With only ten bank clusters, bank-clustered standard errors may be unreliable; Cameron and Miller (2015) recommend 30–50 clusters for asymptotic inference. Consequently, the reported p -values should be regarded as approximate. Future research should utilize wild-cluster bootstrap methods (Cameron, Gelbach, & Miller, 2008) for more robust inference. Furthermore, the negative CRAR coefficient observed in all specifications ($\beta \approx -11$ to -14) reflects a simultaneity issue rather than a genuine negative effect: banks tend to build capital in response to declining stability (through provisioning and recapitalisation during stress), causing the within-bank fixed-effects estimate to conflate regulatory response with underlying stress. This endogeneity concern affects all fixed-effects estimates and would require an instrumental-variable or system-GMM approach for definitive resolution.

Table 3: Panel Regression

Variable	Baseline	P	Levels + Interaction	p	Excess + Interaction	p	Δ Change + Interaction	p
Capital	-13.71***	0.0000	-14.43***	0.0002	-13.86***	0.0001	-11.70***	0.0001
Liquidity	1.60**	0.0291	1.77	0.1527	2.05	0.1469	0.97	0.1758
D_ILFS	26.05	0.6997	—	—	—	—	—	—
D_COV1	40.44	0.538	—	—	—	—	—	—

		1						
D_COV2	8.01	0.573 3	—	—	—	—	—	—
D_SHOCK	—	—	0.74	0.992 7	19.04	0.619 5	32.78	0.325 0
Capital×Shock	—	—	1.33	0.768 1	0.72	0.884 1	21.55***	0.001 1
GNPA	- 19.60** *	0.000 0	-19.46***	0.000 0	-19.75***	0.000 0	-15.86**	0.011 8
SIZE	- 131.06**	0.014 2	-134.16***	0.002 4	-144.55***	0.001 6	-130.10**	0.046 1
F-stat	1.88	0.088 5	2.16	0.058 3	2.22	0.052 4	2.01	0.076 5
R ² within	0.1725		0.1685		0.1722		0.1589	
N	80		80		80		70	

Entity FE; bank-clustered SE (10 clusters). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Baseline: CRAR, LCR, individual shock dummies, GNPA, SIZE (no interaction term; H2 evidence). Levels + Interaction: adds $CRAR \times D_SHOCK$. Excess + Interaction: replaces CRAR with CRAR_excess (CRAR minus time-varying regulatory minimum); adds $CRAR_excess \times D_SHOCK$. Δ Change + Interaction: replaces levels with year-on-year changes ($\Delta CRAR$, ΔLCR); adds $\Delta CRAR \times D_SHOCK$ (primary antifragility test).

The overall F-statistic is marginally significant across specifications (Baseline: $F = 1.88$, $p = 0.089$; Levels: $F = 2.16$, $p = 0.058$; Excess: $F = 2.22$, $p = 0.052$; Change: $F = 2.01$, $p = 0.076$), reflecting the inclusion of theoretically necessary but individually insignificant constituent terms (D_SHOCK , liquidity variable) that dilute the joint test. The coefficients of primary interest — the capital variable, GNPA, and the antifragility interaction — are individually significant at conventional levels, and the $\Delta CRAR \times Shock$ interaction achieves $p = 0.001$. The central finding emerges from the Capital $\times$ Shock row. In the levels specification, the $CRAR \times Shock$ interaction is insignificant ($\beta = 1.33$, $p = 0.768$): pre-existing capital does not become more protective during shocks. The excess-buffer result is identical ($\beta = 0.72$, $p = 0.884$). **However, in the change specification, $\Delta CRAR \times Shock$ is significant ($\beta = 21.55$, $p = 0.001$).** Banks that increased CRAR during shock periods are associated with substantially higher Z-scores. The net effect of $\Delta CRAR$ during shocks is $-11.70 + 21.55 = +9.85$, meaning capital-building during shocks is associated with higher, not lower, stability. This pattern is consistent with the hormesis mechanism described by Taleb (2012), though the fixed-effects design cannot rule out reverse causality: banks that are stabilising for other reasons may simultaneously rebuild capital.

Across all three specifications, GNPA is the most consistently significant and economically the largest predictor of Z-score stability. Its coefficient ranges from -15.86 ($p = 0.012$, change specification) to -19.75 ($p < 0.001$, excess specification), substantially exceeding the magnitude of the capital variable coefficients in absolute terms. A one-percentage-point increase in GNPA is associated with a 16-to-20-point decline in Z-score, whereas a one-percentage-point increase in CRAR (in its most favourable specification, the shock-period change) is associated with only a 9.85-point increase. This asymmetry indicates that asset-quality deterioration destroys stability approximately twice as fast as capital-building creates it — a finding with direct

implications for the relative emphasis regulators should place on asset-quality supervision versus capital supervision.

To test H₄, the CRAR × Ownership interaction was estimated in the levels specification. The coefficient is positive ($\beta = 17.62$, $p = 0.2368$), indicating that PSBs derive greater stability from capital than private banks, but the result does not achieve statistical significance. The Spearman correlation analysis corroborates this direction: PSB CRAR–Z-Score $r_s = 0.6381$ ($p < 0.001$) versus Private $r_s = 0.2496$ ($p = 0.120$). The consistent directional evidence across both interaction and correlation analyses suggests a genuine ownership-moderated effect, but the current sample lacks power to confirm it statistically (five entities per subgroup).

4.4 Hypothesis Summary

H₁ — Supported. All six core study variables differ significantly ($p < 0.01$).

H₂ — Partially supported. LCR predicts stability in the baseline specification ($\beta = 1.60$, $p = 0.029$); this significance attenuates when the shock interaction term is introduced ($p = 0.147$ – 0.176 across the three interaction models), suggesting that D_SHOCK absorbs part of the variation LCR captures in the baseline — likely because liquidity buffers and shock periods are partially correlated through RBI's liquidity management interventions during stress. CRAR shows a non-linear association (Spearman $r_s = 0.638$, $p < 0.001$ for PSBs), but the within-bank FE estimate is confounded by simultaneity.

H₃ — Supported through the dynamic channel ($\Delta\text{CRAR} \times \text{Shock}$: $\beta = 21.55$, $p = 0.001$); not supported through the static channel (CRAR × Shock: $\beta = 1.33$, $p = 0.768$; CRAR_{excess} × Shock: $\beta = 0.72$, $p = 0.884$).

H₄ — Directionally supported (positive CRAR × Ownership coefficients across specifications; Spearman divergence) **but statistically unconfirmed** due to insufficient power (five entities per subgroup).

5. Discussion and Conclusion

5.1 Static vs Dynamic Antifragility

The principal finding is that antifragility in Indian banking operates through the dynamic channel, specifically buffer-building behavior during shocks, rather than through the static channel of pre-existing buffer levels. Pre-shock capital stocks provide a consistent contribution to stability that does not intensify during periods of stress. In contrast, increasing capital during shocks is associated with significantly higher stability. This pattern aligns with Taleb's (2012) hormesis mechanism and the capital-survival channel described by Berger and Bouwman (2013). However, the evidence should be interpreted as associational rather than definitively causal, due to the simultaneity concern discussed in Section 4.3. Establishing causation would require an instrumental-variable or system-GMM approach using lagged capital ratios as instruments.

The design of the Capital Conservation Buffer, which restricts dividend distributions when capital falls below the buffer threshold, serves as the specific regulatory mechanism that plausibly activates dynamic antifragility. This requirement compels banks to use retained earnings to rebuild capital during periods of stress, resulting in adaptive strengthening. The finding that static buffers function equally well in both shock and non-shock periods helps explain the resilience of India's banking system during three major shocks. The antifragility



finding further clarifies why PSBs emerged from the NPA crisis structurally stronger, as the rebuilding process prompted governance reforms and enhancements in risk management beyond the mechanical increase in capital.

5.2 Policy Implications

Three implications follow. First, $\Delta\text{CRAR} \times \text{Shock}$ significance implies that Basel III's capital conservation architecture — the requirement to rebuild buffers after drawing them down — is the framework's most consequential stability mechanism. Second, the dominant role of GNPA ($\beta \approx -16$ to -20 across specifications) implies that asset-quality supervision remains more important than capital supervision for stability — supporting the RBI's post-2015 approach. Third, the Pearson–Spearman divergence suggests that uniform CRAR calibration may be suboptimal for structurally heterogeneous banking systems.

5.3 NAVI Relevance and Limitations

The findings engage each dimension of the NAVI framework. The antifragility effect is inherently non-linear (capital-building produces different stability effects in shock vs calm periods). The NPA resolution cycle was accelerated (compressing a decade of deferred stress into four years). The IL&FS crisis demonstrated interconnectedness (propagation from one entity through the NBFC sector to bank balance sheets). The regulatory response was volatile (alternating between stringent AQR enforcement and COVID-era forbearance).

Limitations include the short, narrow panel (10 banks, 7–8 analysis years), limiting statistical power. The 10-cluster structure renders bank-clustered standard errors approximate (Cameron & Miller, 2015). Reverse causality cannot be excluded: banks increasing capital may be stabilising for independent reasons. Future research should employ system-GMM or wild-cluster bootstrap (Cameron et al., 2008), expand the sample, and develop a continuous antifragility index.

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