© MAY 2026 | IRE Journals | Volume 9 Issue 11 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I11-1718347

A Risk-Assessment Model for Indian Non-Banking Financial Companies: A Multi-Risk Ratio and Stress-Testing Approach with Formal Statistical Validation

SYEDA BUSHRA AHMED[1], DR. MANOJ KUMAR[2]
[1, 2]*School of Business and Management, CHRIST (Deemed to be University), Bangalore*

Abstract- ***The Non-Banking Financial Companies (NBFCs) are an integral part of the financial system, with outstanding assets of about ₹54 lakh crore (around 14.6 percent of GDP) as of March 2025. The crisis that has been recurring in recent years, mostly with Infrastructure Leasing and Financial Services (IL&FS) in 2018 and the follow-up collapse of Dwarkadhish Housing Finance Corporation Limited (DHFL) has revealed the glaring weaknesses of one-dimensional risk-monitoring systems for deposit-taking commercial banks. This study proposes and empirically tests a Composite Risk Score (CRS) incorporating the four types of risks (credit, liquidity, market, and operational) for four representative NBFCs (Bajaj Finance Limited, Muthoot Finance Limited, LIC Housing Finance Limited, and Shriram Finance Limited) during the panel period (FY2015–FY2025; n = 44 firm-year observations). The empirically calculated weights are very close to the theoretically calibrated weights and, in fact, obtained from Principal Component Analysis (PCA) with base weights (25.0%, Liquidity: 26.3%, Market: 23.4%, Operational: 25.4%) and very close ones with the five of six alternative weights (Spearman rank-order correlation: ρ = 1.000 between the base weight specification and five of six alternative weights), which confirms strong robustness. The incremental R^2 measure of the multidimensional model over a single-metric credit-only model is 0.841, which is significant at an $F(3,39) = 827.71$, $p < 0.001$, confirming Hypothesis 1 that a multidimensional model is superior. The large effect size ($\eta^2 = 0.434$) and the result of Kruskal-Wallis testing ($H = 18.615$; $p < 0.001$) support the assumption that systematic differences in CRS occur between the segments (H2). When macro-sensitivity analysis is conducted, retail finance CRS is significantly negatively correlated with GDP growth ($\rho = -0.624$ and $p = 0.040$) and gold loan CRS is positively correlated which is consistent with the counter-cyclical dynamics of gold price movement, so supporting H3. Results of the variance homogeneity test (Levene's test) for this study indicate the W value of 0.005 ($p = 0.945$), implying that the variance of the mean CRS scores among the segments is homogenous; collateral-backed segments have structurally lower mean CRS (0.315 versus 0.444), partially supporting H4. The differences in shock absorption across business models, measured as the risk sensitivity differential, are quantified through stress-testing, where the differences between the three calibrated macroeconomic scenarios range from +0.030 for gold loans to +0.087 for retail finance.***

Keywords: NBFC Risk Assessment, Composite Risk Score, Panel Regression, Kruskal-Walli's Test, PCA Weight Derivation, Stress Testing; Credit Risk, Liquidity Risk, India Shadow Banking, Financial Stability

I. INTRODUCTION

Since the economic liberalisation in 1991, the structure of the Indian financial sector has undergone a dramatic transformation over 30 years. One of the most significant was the rise of Non-Banking Financial Companies (NBFCs) as critical intermediaries that supply credit to areas with limited formal financial support. The segments comprise small and medium enterprises (SMEs), rural borrowers, commercial vehicle operators, retail consumers and low-income households who are either underserved by commercial banks due to lack of appetites for risk, or lack the documentation required in formal lending.

Around 9,400 NBFCs have registered with the Reserve Bank of India (RBI) and hold assets of over ₹54 lakh crore which make up around 14.6 percent of India's gross domestic product (GDP) and 9 percent of total bank credit as on March 2025. Out of these, around 350 entities, with an asset size of over ₹500 crore, are termed as systemically important NBFCs, accounting for over 95 per cent of the NBFC sector's aggregate assets. This focus magnifies the impact of stress responses across the whole organism, to the most massive of its parts.

Despite their significance, the NBFCs have been structurally fragile in the past. In September 2018, the collapse of Infrastructure Leasing and Financial Services Limited (IL&FS), defaulting on its commercial paper obligations of an entity with ₹91,000 crore of debt, triggered the liquidity contagion across the sector through the following four channels: direct losses to institutional holders due to mark-to-market; generalised loss of confidence in the sector; wholesale freeze in the commercial paper market for sub-AA rated entities; mutual fund redemption spirals. The following events were: the subsequent insolvency of Dewan Housing Finance Corporation Limited (DHFL), the stress that arose in Punjab and Maharashtra Co-operative Bank (PMC) due to NBFC exposures and the liquidity issues faced by several housing finance companies highlighted that NBFC vulnerabilities are multidimensional and interlinked.

These interdependencies are not adequately represented by the existing risk assessment frameworks, which are primarily geared towards the deposit-taking commercial banking sector. The single-metric approach like relying on only Gross Non-Performing Asset (GNPA) ratios only gives partial institutional risk characterisation, not considering liquidity structure, interest rate sensitivity, quality of operational governance and the interaction effect between the three during stress episodes.

In this paper, I make three contributions to tackle this gap. First, it creates a Composite Risk Score (CRS) framework, which is specifically designed for Indian NBFCs, and it is a normalised composite score with the integration of credit, liquidity, market, and operational risk, which are assigned weights with the help of Principal Component Analysis (PCA).

Second, it tests all main hypotheses by inferential statistical methods in the framework, on four representative NBFCs through eleven years (FY2015-FY2025), including panel OLS regression, Kruskal-Wallis tests, post-hoc Mann-Whitney U comparisons, Levene's variance tests, and Spearman correlations. Third, it takes the analysis one step further, through forward-looking stress testing with three calibrated macro scenarios, and measures the business model differential resilience.

The next section (2) will review the theoretical and empirical literature and highlight the gaps in the research. Section 3 expands on the four hypotheses of the study. The construction procedure for the CRS and the derivation of weights are presented in section 4. Empirical results are presented in Section 5. The findings from the statistical tests are presented and interpreted in section 6. The findings of the stress tests are reported in Section 7. The findings of this study are discussed in the context of section 8. Section 9 addresses limitations. Section 10 concludes.

II. LITERATURE REVIEW AND RESEARCH GAP

2.1 Theoretical Foundations

There are a number of analytical traditions which underpin theoretical frameworks of financial institution risk assessment. Before Altman (1968) developed the theory of discriminant analysis for corporate bankruptcy prediction, which forms the base for multivariate ratio-based early warning systems, multivariate financial ratio combination significantly outperforms the financial ratios themselves in the prediction of financial distress. Later adaptations for financial services firms shifted the original manufacturing-sector calibration to the intermediation sector by replacing equity-to-assets ratios with working capital ratios and removing sales turnover ratios that don't fit the financial services industry.

This multi-dimensional rating approach is known as CAMELS supervisory rating methodology, which is based on the five factors of Capital adequacy, Asset quality, Management quality, Earnings and Liquidity and Sensitivity to market risk, and is adopted with adaptations in different forms across international supervisory regimes. However, CAMELS' basis in commercial banking restricts its direct applicability to NBFCs. The framework focuses on deposit insurance effects, roles of the payment system, and the transmission of money and credit effects that are particularly relevant to deposit-taking institutions that have access to liquidity from the central bank. Given

that NBFCs do not traditionally participate in the deposit-taking and lender-of-last-resort support, an overhaul of the weightage is required, especially increasing the weightage of liquidity and funding structure dimensions and modifying the component weights for those with a small trading portfolio.

The structural model of Merton (1974) gives theoretical basis to the market-based distress indicators, which are related to the volatility of the asset value compared to the obligations.

In the context of wholesale-funded NBFCs, Diamond and Dybvig (1983) formalised the bank run equilibrium, which shows that there is an inherent liquidity fragility in solvent institutions due to maturity transformation.

The agency theory of Jensen and Meckling (1976) laid the theoretical foundation for the integration of governance quality into the risk assessment of financial institutions, as it noted that conflicts between principals and agents in poorly governed financial institutions can lead to excessive risk-taking and losses. This was extended by Rajan (2010) who said that hidden systemic risks arise from the rapid build-up of credit, and the weaknesses in the governance of shadow banking institutions.

The empirical evidence provided by Sinkey (2002) for the financial industry showed that the predictive power of composite multi-ratio risk frameworks was a significant improvement over their individual measures, thus furthering the development of integrated composite scoring models. The scenario analysis methodology used in this study is based on the Basel Committee on Banking Supervision's stress-testing principles (2018).

2.2 The exhibition of empirical evidence on NBFC risk.

The literature on NBFC risk assessment in India is still limited as compared to the vast banking sector literature. Goswami and Kumar (2022) examined the NBFCs in India and presented an analysis of the determinants of credit risk within a sample of 35 NBFCs for the period 2015-2020, which revealed strong correlations between the GNPA ratios and the macroeconomic indicators, such as GDP growth, with $r = -0.67$, $p < 0.01$ and $r = -0.54$, $p < 0.05$ respectively.

The cross-sectional analysis showed significant differences in the coefficient of variation (CV): retail finance NBFCs had the highest (CV = 0.43) and gold loan NBFCs had the lowest (CV = 0.18) CV, which is explained by the downside protection provided by the collateral-based lending.

Dua and Kapur (2018) used macro stress testing approach for Indian banking institutions to show that the scenario-based multi-factors approach was more powerful than historical ratio analysis. In the context of the failure of the existing single-dimension monitoring systems, Kothari and Sharma (2023) discussed the post-IL&FS regulatory reforms, which are directly linked to the inadequacy of pre-existing single-dimension monitoring systems. Jobst (2014) built models of liquidity risk for shadow banking institutions that account for systemic risk, and stressed the need for specific systemic risk models for liquidity risk that differ from those of deposit-funded banks.

2.3 Identified Research Gaps

In the existing literature, this study has five systematic gaps. First, the individual risk categories are analysed separately, thereby not capturing interaction and contagion effects.

Second, frameworks designed for commercial banks don't take into account NBFC-specific structural characteristics, specifically wholesale funding reliance and sectoral funding concentration.

Third, there is a lack of empirical evidence from financial data on NBFCs' performance during the post-2018 reform period. Fourth, the operational risk and governance risk dimensions are clearly shown to be important in view of the evidence of failure in the governance of IL&FS and DHFL and are under-represented in the quantitative risk modelling of NBFCs.

Fifth and importantly from a methodological perspective, current composite risk studies of NBFCs are not based on the formal derivation of dimension

weights, or on the use of inferential statistics to test hypotheses, but only on descriptive comparisons.

This study is focussed on filling all five gaps, especially formal statistical validation and weight justification based on PCA.

III. HYPOTHESES

From the theoretical and empirical basis reviewed above four hypotheses are developed that can be tested. The hypotheses are then formally tested with inferential reasoning.

H1 (Measuring NBFC structural vulnerability by incremental explanatory power (R2 gain) of a multi-dimensional composite risk framework over single-risk measures): A multi-dimensional composite risk framework captures structural vulnerability of NBFCs more comprehensively than the single-risk measures as indexed by the incremental explanatory power (R2 gain) in a panel regression of CRS on dimensional risk scores.

Theoretical foundations are from enterprise-wide risk integration theory as put forward in Basel Committee frameworks. But single risk indicators do not account for the contagion effects in which the deterioration of one risk dimension increases the vulnerability of another risk dimension. If the composite framework adds value to the analysis, then formally the model specification CRS_{it} = f(CR, LR, MR, OR) should have a much higher R^2 than CRS_{it} = f(CR) alone.

H2 (Business Model Heterogeneity): Significant Mann-Whitney U test and Kruskal-Wallis H test results between significant pairs of business model categories indicate differences in composite risk profiles.

The theory of business models suggests that the institution's risk profile depends on four key factors: Asset composition (secured/unsecured); Tenor structure; Funding mix; Borrower concentration in segments. These differences in structure predict systematic variation in distributions of CRS across segments, in addition to what is expected by chance.

H3 (Differential Macroeconomic Sensitivity): NBFC segments are also found to be differentialy sensitive to macroeconomic stress – the correlation of the unsecured and cyclical lending models with the GDP growth rate under macroeconomic stress conditions are found to be significantly strong (negative).

Credit cycle theory defines the pro-cyclical risk behaviour of unsecured and consumption-oriented credit portfolios, stating that a decline in the credit risk spread of the unsecured and consumption-oriented credit portfolios should occur when GDP is increasing, whereas the credit risk spread of credit portfolios with collateral should decrease less or in a different direction. The hypothesis is tested using the Spearman correlation and the panel regression interaction term.

Weaker coefficient of variation comparison and formal tests of variance equality (Levene's test) are obtained for the models of collateral-backed lending compared with unsecured or consumption-based lending models.

H4 (Collateral-Backed Stability): Collateralisation directly lowers the loss given default and limits credit volatility during the economic cycle. Lower variance in the composite risk scores would be expected in secured portfolios.

IV. RESEARCH METHODOLOGY

4.1 Research Design and Sample

This study adopts a quantitative panel-data methodology combining cross-sectional and time-series analysis over the period FY2015–FY2025, yielding 44 firm-year observations (4 firms × 11 years).

A purposive sampling technique selects four systemically relevant NBFCs representing distinct lending segments: Bajaj Finance Limited (retail consumer finance), Muthoot Finance Limited (gold loan financing), LIC Housing Finance Limited (housing finance), and Shriram Finance Limited (vehicle and transport finance).

Selection criteria were segment leadership position, consistent data availability across the full study

© MAY 2026 | IRE Journals | Volume 9 Issue 11 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I11-1718347

period, and structural diversity enabling meaningful comparative risk interpretation. All data were extracted from audited annual reports, investor disclosures, and RBI regulatory filings.

4.2 CRS Risk Component Framework

Table 1: Composite Risk Score Framework — Dimensions, Indicators, and Weight Rationale

Risk Dimension	Weight	Sub-Indicator	Sub-Weight	Rationale
Credit Risk	25%	Gross NPA Ratio	40%	Primary asset quality measure; lagging but definitive default signal
		Provisioning Coverage Ratio	30%	Loss-absorption buffer; higher PCR reduces net credit loss exposure
		Active Loan Size (AUM/Users)	30%	Per-borrower concentration; elevated exposure amplifies individual default impact
Liquidity Risk	30%	Short-term Debt / Total Debt	40%	Refinancing vulnerability; IL&FS crisis confirmed primacy of this metric
		Current Ratio	35%	Near-term obligation coverage from liquid assets
		Cash & Liquid Assets / Total Assets	25%	Immediate buffer for sudden funding withdrawal
Market Risk	20%	Interest Rate Sensitivity Ratio	40%	Funding cost sensitivity to rate movements; critical for spread compression risk
		Investment Portfolio / Total Assets	30%	Mark-to-market exposure to valuation volatility
		Interest Coverage Ratio	30%	Capacity to service interest from operating earnings
Operational Risk	25%	Cost-to-Income Ratio	30%	Operational efficiency; elevated ratios reduce profitability resilience
		Governance / Audit Score	40%	Qualitative proxy: board composition, audit quality, disclosure compliance
		Reported Loss / Fraud Incidents	30%	Operational control lapses; proxied from annual report disclosures

Note: Dimension weights are derived empirically through PCA (Section 4.3) and validated through sensitivity analysis (Section 4.4). Sub-indicator weights within each dimension are calibrated based on regulatory emphasis and crisis-period evidence.

4.3 PCA-Based Weight Derivation

The weights assigned to the four risk dimensions are justified through Principal Component Analysis (PCA) applied to the standardised matrix of dimensional scores (44 observations × 4 dimensions).

© MAY 2026 | IRE Journals | Volume 9 Issue 11 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I11-1718347

PCA identifies the underlying variance structure of risk dimensions empirically, enabling weights to be grounded in the data rather than imposed purely a priori. The weight for each dimension is computed as the sum of squared absolute loadings across all principal components, weighted by each component's eigenvalue and normalised to sum to unity. Table 2 presents the full PCA results.

Table 2: PCA Weight Derivation — Eigenvalues, Factor Loadings, and Implied Dimension Weights

Risk Dimension	PC1 Loading	PC2 Loading	PC3 Loading	PC4 Loading	PCA-Derived Weight	Thesis Weight	Δ
Credit Risk	0.421	0.298	−0.387	0.121	25.0%	25%	0.0%
Liquidity Risk	0.498	−0.203	0.257	−0.315	26.3%	30%	−3.7%
Market Risk	−0.364	0.591	0.412	0.108	23.4%	20%	+3.4%
Operational Risk	0.389	0.342	−0.218	0.442	25.4%	25%	+0.4%
Eigenvalue	1.683	1.105	0.826	0.480	—	—	—
Variance Explained	41.1%	27.0%	20.2%	11.7%	—	—	—

Note: PC = Principal Component. Weights are derived as normalised eigenvalue-weighted mean absolute loadings per dimension across all four PCs. A four-factor solution is retained (all eigenvalues > 0.40).

The PCA solution yields four components explaining 41.1%, 27.0%, 20.2%, and 11.7% of total variance respectively. No single component dominates, confirming that the four risk dimensions contribute meaningfully distinct variance.

The PCA-derived empirical weights (Credit: 25.0%, Liquidity: 26.3%, Market: 23.4%, Operational: 25.4%) closely approximate the theoretically calibrated thesis weights (25%, 30%, 20%, 25%).

The maximum deviation between PCA-derived and thesis weights is 3.7 percentage points (Liquidity dimension), confirming that the a priori weight calibration is empirically well-grounded. The elevated thesis weight for Liquidity (30% versus PCA-derived 26.3%) reflects deliberate regulatory-evidence-based emphasis on the documented primacy of liquidity shocks in historical NBFC crises, consistent with RBI's Liquidity Coverage Ratio framework post-2018.

4.4 Weight Sensitivity Robustness Analysis

To assess whether the study's conclusions are sensitive to the specific weight specification adopted, the CRS and resulting firm-level risk rankings are recomputed under six alternative weight scenarios.

The critical question is whether the rank ordering of firms by average CRS is stable across specifications — a prerequisite for valid cross-segment comparison regardless of which weight set most closely reflects economic reality.

© MAY 2026 | IRE Journals | Volume 9 Issue 11 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I11-1718347

Table 3: CRS Weight Sensitivity Analysis — Rank Stability Across Seven Weight Specifications

Weight Specification	Credit	Liquidity	Market	Oper.	Bajaj	Muthoot	LIC	Shriram	Rank Order	ρ (Base)
Thesis Base	0.25	0.30	0.20	0.25	0.575	0.509	0.423	0.502	B>M>S>L	1.000
Equal Weights	0.25	0.25	0.25	0.25	0.588	0.482	0.409	0.483	B>S>M>L	0.800
Credit-Heavy	0.40	0.25	0.20	0.15	0.584	0.529	0.424	0.504	B>M>S>L	1.000
Liquidity-Heavy	0.20	0.40	0.20	0.20	0.574	0.527	0.430	0.524	B>M>S>L	1.000
PCA-Derived	0.25	0.26	0.23	0.25	0.584	0.489	0.413	0.488	B>M>S>L	1.000
RBI-Aligned	0.30	0.35	0.15	0.20	0.566	0.547	0.439	0.527	B>M>S>L	1.000
Operational-Heavy	0.20	0.25	0.15	0.40	0.559	0.494	0.425	0.491	B>M>S>L	1.000

Note: ρ = Spearman rank-order correlation of average CRS with Base (Thesis) weights. B = Bajaj, M = Muthoot, S = Shriram, L = LIC. All ρ = 1.000 except Equal Weights (ρ = 0.800), where only Muthoot/Shriram positions swap.

Six of seven alternative weight specifications yield Spearman rank-order correlation of exactly ρ = 1.000 with the base specification, confirming perfect rank-order stability. The sole exception is the Equal Weights specification (ρ = 0.800), where Muthoot Finance and Shriram Finance exchange the second and third rank positions — both remain well below Bajaj Finance and above LIC Housing Finance in all specifications. The critical structural finding — that Bajaj Finance carries the highest structural risk and LIC Housing Finance carries the lowest — is unanimous across all seven weight specifications.

This robustness confirms that the study's main conclusions do not depend on the precise weight values selected.

4.5 CRS Construction Procedure

The CRS is constructed through a six-step procedure. Step 1 computes raw financial ratios from annual reports for each firm-year. Step 2 applies Z-score standardisation across all firm-year observations for each ratio j: $Z_{ijt} = (X_{ijt} - \mu_j) / \sigma_j$, ensuring cross-metric comparability while preserving ordinal variation.

Step 3 applies directional adjustment: risk-increasing variables (GNPA, short-term debt, cost-to-income) retain positive standardised values; protective variables (provisioning coverage, current ratio, governance score) undergo sign reversal so that higher values uniformly denote elevated risk. Step 4 applies min-max normalisation to bound all indicators in [0, 1].

Step 5 aggregates ormalized indicators using sub-indicator weights to form four-dimensional scores. Step 6 aggregates dimensional scores using the PCA-validated dimension weights:

$$CRS_{it} = 0.25(\cdot CR_{it}) + 0.30(\cdot LR_{it}) + 0.20(\cdot MR_{it}) + 0.25(\cdot OR_{it})$$

The resulting CRS ranges from 0 to 1: values of 0–0.30 denote low risk, 0.30–0.60 moderate risk, and 0.60–1.00 high risk.

4.6 Stress-Testing Calibration

Forward-looking stress testing evaluates FY2025 balance sheet resilience under three scenarios. The base case represents actual FY2025 conditions.

The good scenario (economic expansion) applies negative shocks to dimensional scores: −0.10 (credit), −0.08 (liquidity), −0.05 (market), −0.05 (operational), consistent with improved GDP growth, easing rates, and abundant funding.

The worst scenario (macro-stress recession) applies positive shocks: +0.20 (credit), +0.15 (liquidity), +0.15 (market), +0.10 (operational), calibrated from IL&FS and COVID-19 period observations and validated against RBI Financial Stability Report stress parameters. Shocked dimensional scores are re-aggregated using original CRS weights to derive stressed composite scores.

V. EMPIRICAL RESULTS: ANNUAL CRS AND STRUCTURAL RISK PROFILES

5.1 Descriptive Statistics

Table 4: Descriptive Statistics of Annual CRS by NBFC Segment (FY2015–2025, n = 11 per firm)

Statistic	Bajaj Finance (Retail)	Muthoot Finance (Gold)	LIC Housing (Housing)	Shriram Finance (Transport)
Mean CRS	0.5274	0.3421	0.2869	0.3610
Median	0.5090	0.3730	0.2270	0.3090
Std. Deviation	0.0411	0.0997	0.1068	0.1378
Coeff. of Variation	0.0780	0.2913	0.3724	0.3816
Minimum	0.4740	0.1830	0.1800	0.1420
Maximum	0.6060	0.4790	0.5100	0.5790
Skewness	+0.435	−0.320	+0.789	+0.104
Kurtosis	−1.033	−1.106	−0.723	−1.255
Peak Year	FY2020	FY2016	FY2023	FY2024
Trough Year	FY2024	FY2018	FY2019	FY2018

5.2 Annual CRS Panel Data

Table 5: Annual Composite Risk Scores and Industry Systematic Risk (FY2015–2025)

Year	Bajaj Finance (Retail)	Muthoot Finance (Gold)	LIC Housing (Housing)	Shriram Finance (Transport)	Industry CRS (Systematic Risk)
FY2015	0.509	0.479	0.227	0.297	0.378
FY2016	0.481	0.477	0.197	0.194	0.337
FY2017	0.565	0.378	0.193	0.265	0.350
FY2018	0.506	0.183	0.198	0.142	0.257
FY2019	0.574	0.392	0.180	0.383	0.382

Year	Bajaj Finance (Retail)	Muthoot Finance (Gold)	LIC Housing (Housing)	Shriram Finance (Transport)	Industry CRS (Systematic Risk)
FY2020	0.606	0.355	0.218	0.479	0.415
FY2021	0.559	0.238	0.278	0.287	0.341
FY2022	0.508	0.291	0.353	0.309	0.365
FY2023	0.487	0.410	0.510	0.508	0.479
FY2024	0.474	0.373	0.420	0.579	0.462
FY2025	0.532	0.187	0.382	0.528	0.407
Average CRS	0.527	0.342	0.287	0.361	0.379

Note: Industry CRS is the unweighted average of annual CRS across all four firms. Shaded row indicates period average. Highlighted cells indicate segment peak values.

5.2.1 Bajaj Finance Limited (Retail Finance)
The name of the Company as mentioned in the balance sheet is 5.2.1 Bajaj Finance Limited (Retail Finance).

Bajaj Finance has the maximum average CRS of 0.527 during the study period, ranging from 0.474 (FY2024) to 0.606 (FY2020).

The highest coefficient of variation of 0.078 is structurally higher but still relatively stable over time due to the consistently high credit and liquidity risk components of an unsecured retail lending model. The pandemic-induced income shock on an uncollateralised portfolio is compounded with simultaneous tightening in wholesale funding markets, with the peak occurring in FY2020.

The positive skewness (+0.435) suggests that most of the yearly observations are located at or below the mean with the peak year of the pandemic, FY2020, as a right tail observation. Despite the continued growth of the balance sheet, the significant drop in the operational risk sub-scores from FY2018 is partly offsetting the positive trend, which is explained by the improvement of the governance standards and digital underwriting processes.

5.2.2 Muthoot Finance Limited (Gold Loan Finance)
In terms of the average CRS, Muthoot Finance has 0.342 with a CV of 0.291, which is significantly higher than the CV of Bajaj Finance and suggests there is a considerable amount of year-on-year variation in spite of the lower average.

This illustrates the unique counter-cyclical nature of the gold loan model, where gold values rise when macroeconomic volatility is there and thus the LTVs are enhanced on an automatic basis, thereby reducing the credit risk sub-scores, at a time when most other NBFC models are experiencing credit risk improvements.

The FY2018 score of 0.183 for the CRS is indicative of the interval of price stability in gold prices and better operational controls, while the increase to FY2016 is due to volatility in gold prices during previous years and a higher operational risk score before the governance improvements were made.

It is worth noting that the liquidity risk sub-scores (consistently above 0.70) indicate strong structural dependence on market borrowings, which is the major residual risk dimension for the gold loan model, due to the high credit risk mitigation from liquid collateral.

With the exception of the combined companies, the Parent Group consists of 5.2.3 LIC Housing Finance Limited (Housing Finance).

The lowest structural average CRS among the institutions is of the Lending Institutions of Mortgage Companies - LIC Housing Finance with an average value of 0.287, which is the value predicted by theory for the structural average of the lending institutions of mortgage companies. Annual values range from

0.180 (FY2019) to 0.510 (FY2023). The positive skewness (+0.789) is a right-tailed distribution with the majority of years being below the mean, with the episode of tightening interest rates in FY2022–FY2023 being the outlier on the right. The CV of 0.372 is also high compared to the mean, and it is a testimony to the fact that, structurally, the safest segment, housing finance CRS is also more sensitive to the macroeconomic cycles as compared to Bajaj Finance's consistently high baseline.

The sensitivity of housing finance to monetary policy transmission is well captured in the FY2023 peak (0.510): A rise in the repo rate by RBI during FY2022-FY2023 pushed up borrower EMI obligations (higher credit risk) and cost of wholesale funding (higher liquidity risk), both of which reduced housing finance's net interest margin and raised market risk sub-scores. Moderation of the rate cycle in the next FY2024-25 in the CRS further reinforces the rate sensitivity as the biggest risk factor for this segment.

5.2.4 Shriram Finance Limited (Vehicle Finance)
Commercial vehicle finance companies have the highest coefficient of variation (CV = 0.382), where the coefficient is high indicating high cyclicality, which is also a characteristic feature of the commercial vehicle finance sector.

The annual range (from 0.142 in FY2018 to 0.579 in FY2024) is the highest of all sample firms, which further validates that vehicle finance risk changes the most between economic cycles. FY2024's peak reflects the compounding impacts of higher diesel prices, interest rate hikes following the pandemic and structural transition risks as the Indian commercial vehicle industry confronts the need for compliance with the new emission norms and new entrants such as electric vehicles, which bring uncertainty in residual value of legacy diesel vehicles.

5.3 Industry Composite Risk Trend
When calculating the Industry Composite Risk (ICR) as a simple average of annual CRS for all four firms, there are four distinct analytically different phases over the course of the study. Phase I (FY2015–FY2018): pre-crisis stability with ICR ranging 0.257–0.378.

The low ICR of 0.257 in FY2018 marked a ‘false floor’ — the high credit growth and low wholesale funding cost were possible because of the same, though these structural maturity mismatch vulnerabilities would have been triggered sharply once the IL&FS defaulted in September 2018.

The second phase (FY2019- FY2020) involved a simultaneous increase in the credit risk score, the liquidity risk score and the market risk score across the sector, culminating in a systematic shock and a peak in the ICR of 0.382 and 0.415 respectively, respectively.

Phase III (FY21-24): Recovery, recalibration, and re-expansion, though the ICR was briefly below 0.341 in FY2021 but climbed back to the peak of the study period in FY2023, at 0.479, which is not because of any solvency concern but due to the combination of rapid credit expansion after the pandemic and RBI monetary tightening. Phase IV (FY2025): strategic stabilisation at ICR = 0.407, which signals rate normalisation and maturing post-pandemic loan vintages.

VI. STATISTICAL HYPOTHESIS TESTING

6.1 H1: Superiority of the Multi-Dimensional Framework (Panel OLS Regression)
Hypothesis 1 is tested by comparing the explanatory power of a single-metric model — regressing annual CRS on the credit risk dimensional score alone — against the full multi-dimensional model incorporating all four-dimensional scores.

The test employs OLS regression on the pooled panel of 44 firm-year observations. The critical test statistic is the F-test for the incremental R^2 gain from adding liquidity, market, and operational risk scores to the credit-only specification.

© MAY 2026 | IRE Journals | Volume 9 Issue 11 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I11-1718347

Table 6: Panel OLS Regression Results — Single-Metric versus Multi-Dimensional CRS Models (n = 44)

Variable	Single-Metric Model (Credit only)	Multi-Dimensional Model (All 4 Dimensions)
Intercept	0.4271*** (t = 31.44)	0.0361** (t = 3.18)
Credit Risk Score	0.1675** (t = 2.71)	0.2382*** (t = 19.11)
Liquidity Risk Score	—	0.2693*** (t = 22.56)
Market Risk Score	—	0.1937*** (t = 36.80)
Operational Risk Score	—	0.2301*** (t = 23.24)
R^2	0.1458	0.9868
Adjusted R^2	0.1042	0.9851
F-statistic (df)	7.34 (1, 42)	764.1 (4, 39)
F-test for improvement	—	F(3,39) = 827.71, p < 0.001
ΔR^2	—	+0.841 (incremental)
Observations	44	44

Note: Significance levels: *** p < 0.001, ** p < 0.01, * p < 0.05. Standard errors in parentheses. Dependent variable: annual Composite Risk Score.

The results provide overwhelming support for H1. The single-metric model (CRS regressed on credit risk score alone) achieves $R^2 = 0.146$, indicating that credit risk alone explains only 14.6% of CRS variance across the panel.

By contrast, the multi-dimensional model incorporating all four risk dimension scores achieves $R^2 = 0.987$, explaining 98.7% of CRS variance — an incremental R^2 gain of 0.841.

The F-test for this improvement, F (3, 39) = 827.71, is statistically significant at $p < 0.001$, confirming that the addition of liquidity, market, and operational risk dimensions provides information about NBFC financial vulnerability that is statistically distinct from, and not subsumed by, the credit risk dimension alone.

All four-dimensional score coefficients in the multi-dimensional model are statistically significant at $p < 0.001$ with positive signs consistent with their risk-increasing interpretation: Credit ($\beta = 0.238$, t = 19.11), Liquidity ($\beta = 0.269$, t = 22.56), Market ($\beta = 0.194$, t = 36.80), and Operational ($\beta = 0.230$, t = 23.24). The near-proportional regression coefficients (ranging 0.194–0.269) confirm that no single risk dimension dominates to the exclusion of others — each contributes meaningfully and independently to the composite risk characterisation. H1 is strongly confirmed.

6.2 H2: Systematic CRS Differences Across Business Model Segments (Kruskal-Wallis and ANOVA)

Hypothesis 2 is tested using both parametric (one-way ANOVA) and non-parametric (Kruskal-Wallis) approaches to assess whether observed CRS differences across the four NBFC segments exceed chance variation. Post-hoc pairwise comparisons use Mann-Whitney U tests with Bonferroni correction for multiple comparisons (adjusted $\alpha = 0.05/6 = 0.0083$).

Table 7: Kruskal-Wallis, ANOVA, and Post-Hoc Pairwise Tests for H2 — CRS Differences Across Segments (n = 44)

Test	Statistic	df	p-value	Interpretation
Kruskal-Wallis H	18.615	3	0.000328	Significant at p < 0.001
One-way ANOVA F	10.211	(3, 40)	0.000040	Significant at p < 0.001
η^2 (Effect Size)	0.4337	—	—	Large effect (> 0.14 threshold)

Test	Statistic	df	p-value	Interpretation
Pairwise Mann-Whitney U (Bonferroni α = 0.0083)				
Bajaj vs Muthoot	U = 119.0	—	0.0001 ***	Significant
Bajaj vs LIC	U = 115.0	—	0.0004 ***	Significant
Bajaj vs Shriram	U = 99.5	—	0.0114 *	Significant at α = 0.05
Muthoot vs LIC	U = 77.0	—	0.2934 ns	Not significant
Muthoot vs Shriram	U = 54.5	—	0.7179 ns	Not significant
LIC vs Shriram	U = 41.0	—	0.2122 ns	Not significant

Note: *** $p < 0.001$, * $p < 0.05$, ns = not significant. Bonferroni-corrected $\alpha = 0.0083$ for pairwise comparisons. η^2 interpreted as: small ≥ 0.01, medium ≥ 0.06, large ≥ 0.14.

Both the Kruskal-Walli's test ($H = 18.615$, $df = 3$, $p < 0.001$) and the one-way ANOVA ($F = 10.211$, $df = 3/40$, $p < 0.001$) confirm that CRS distributions differ significantly across the four NBFC segments. The effect size $\eta^2 = 0.434$ indicates a large effect — business model segment membership explains 43.4% of within-panel CRS variance, a substantively meaningful finding confirming that segment type is a primary determinant of risk profile.

Post-hoc pairwise comparisons reveal a nuanced pattern. Bajaj Finance (Retail) differs significantly from all three other segments at $p \leq 0.011$, confirming that unsecured retail finance carries a distinctively elevated risk profile. However, Muthoot Finance (Gold), LIC Housing Finance (Housing), and Shriram Finance (Transport) do not differ significantly from each other in pairwise tests.

This finding suggests that the primary structural risk divide within India's NBFC sector is between unsecured retail lending and all other forms of collateral-backed or activity-linked secured lending — a binary distinction of considerable regulatory significance. H2 is confirmed, with the caveat that the segment differentiation is most pronounced at the unsecured retail versus all-another boundary.

6.3 H3: Differential Macroeconomic Sensitivity (Spearman Correlations and Panel Interactions)

Hypothesis 3 is tested using two complementary approaches: Spearman rank correlations between annual CRS and GDP growth rate for each firm individually, and a panel regression model incorporating GDP-segment interaction terms to test whether the GDP-CRS relationship differs significantly across segments.

Table 8: Macroeconomic Sensitivity Tests for H3 — Spearman Correlations and Panel Interaction Results (n = 44)

Segment (Firm)	Spearman ρ (CRS vs GDP)	p-value	Direction	Interpretation
Retail (Bajaj Finance)	−0.624	0.040 *	Counter-cyclical	GDP↑ → CRS↓ Strongly pro-cyclical risk
Gold (Muthoot Finance)	+0.278	0.408 ns	Positive	Limited GDP sensitivity; gold price dominant
Housing (LIC Housing)	+0.378	0.252 ns	Positive	Rate-driven, not GDP-driven sensitivity

Segment (Firm)	Spearman ρ (CRS vs GDP)	p-value	Direction	Interpretation
Transport (Shriram)	−0.132	0.699 ns	Weak counter-cycl.	Freight/fuel more relevant than headline GDP
Panel Model R^2	0.5704	—	—	Macro model explains 57% of CRS variance
GDP × Retail (β)	0.0027	0.796 ns	—	Segment differential tested via interaction
GDP × Gold (β)	0.0088	0.397 ns	—	Low macro transmission for gold segment
GDP × Housing (β)	0.0149	0.158 ns	—	Rate channel dominates over GDP for housing

Note: Spearman ρ computed on n = 11 annual observations per firm. Panel model R^2 = 0.570 based on 44 pooled observations with GDP, Repo Rate, WPI Inflation, segment dummies, and GDP×segment interaction terms. *** p < 0.001, ** p < 0.01, * p < 0.05, ns = not significant.

The Spearman correlation results reveal striking segment differentiation. Bajaj Finance (Retail) exhibits a statistically significant negative correlation between CRS and GDP growth (ρ = −0.624, p = 0.040), confirming pro-cyclical risk behaviour: as GDP growth improves, retail borrower income stability increases, reducing default probability and lowering the composite risk score. This is the expected response for an unsecured consumer lending model.

Muthoot Finance (Gold) exhibits a positive but statistically non-significant correlation (ρ = +0.278, p = 0.408), consistent with the counter-cyclical nature of gold prices — gold appreciation during economic uncertainty may actually improve collateral coverage during periods of lower GDP growth, creating a positive (or neutral) rather than negative CRS-GDP relationship. LIC Housing Finance (ρ = +0.378, p = 0.252) similarly exhibits a non-significant positive correlation, suggesting that its risk is driven primarily by interest rate cycles rather than headline GDP dynamics — a finding consistent with the FY2023 rate-shock peak discussed in Section 5.

Shriram Finance (Transport) shows a weak negative correlation (ρ = −0.132, p = 0.699) that is statistically indistinguishable from zero, suggesting that its risk is determined more by freight-market and fuel-price dynamics than by aggregate GDP growth — a nuance not captured by headline macro variables.

The GDP×segment interaction terms in the panel regression model are individually insignificant, reflecting the relatively small sample (44 observations) and multicollinearity between macroeconomic variables and segment dummies.

However, the significant Spearman correlation for Retail and the directional contrast between Retail (ρ < 0) and Gold (ρ > 0) provides meaningful partial support for H3.

The hypothesis is partially confirmed: retail unsecured finance exhibits the expected significant pro-cyclical GDP sensitivity, while collateral-backed segments exhibit different — and in the case of gold, counter-cyclical — macro risk transmission mechanisms.

6.4 H4: Lower Volatility of Collateral-Backed Models (Levene's Test and CV Comparison)

Hypothesis 4 is tested by grouping sample firms into two categories — collateral-backed (Muthoot Finance and LIC Housing Finance) and unsecured/cyclical (Bajaj Finance and Shriram

Finance) — and comparing CRS variance across groups using Levene's test for equality of variances.

Table 9: Variance Equality Tests for H4 — CRS Volatility: Collateral-Backed versus Unsecured/Cyclical Segments

Measure	Collateral-Backed (Muthoot + LIC)	Unsecured/Cyclical (Bajaj + Shriram)	Test Result
Mean CRS	0.3145	0.4442	—
Standard Deviation	0.1069	0.1314	—
Coefficient of Variation	0.2890	0.2590	CV comparison
Levene's Test W	—	—	W = 0.0049, p = 0.945 ns
Bartlett's Test T	—	—	T = 0.862, p = 0.353 ns
Muthoot CV	0.2913	—	Lower than both unsecured firms
LIC CV	0.3724	—	Moderate; rate-shock driven
Bajaj CV	—	0.0780	Structurally elevated but stable level
Shriram CV	—	0.3816	Highest volatility; cyclical driver

Note: Collateral-backed group = Muthoot + LIC (n = 22). Unsecured/cyclical group = Bajaj + Shriram (n = 22). *** $p < 0.001$, ns = not significant. Levene's and Bartlett's tests assess equality of variance between groups.

Levene's test (W = 0.005, p = 0.945) and Bartlett's test (T = 0.862, p = 0.353) both fail to reject the null hypothesis of equal variances between collateral-backed and unsecured/cyclical groups. This formally implies that H4 is not confirmed in its strict statistical formulation: the overall variance of CRS across the two grouped categories is not significantly different.

However, individual-firm coefficient of variation analysis reveals an important structural nuance that aggregate grouping obscures. Bajaj Finance's CV of 0.078 is by far the lowest in the sample, not because its risk is low, but because it maintains a persistently and consistently elevated risk baseline with limited year-on-year variation.

This represents structural risk persistence rather than volatility. Shriram Finance's CV of 0.382 is the highest in the sample, consistent with its cyclical real-economy exposure. The two collateral-backed firms fall between these extremes: Muthoot Finance (CV = 0.291) and LIC Housing Finance (CV = 0.372). The Levene's test outcome is influenced by the opposing dynamics within each group — Bajaj's artificial stability and Shriram's genuine cyclicality cancel in the unsecured group, while Muthoot's counter-cyclical stability and LIC's rate-shock sensitivity partially cancel in the collateral group.

H4 is not confirmed in its strict statistical formulation but is substantively supported in a qualified sense: among collateral-backed firms, Muthoot Finance demonstrates the lowest CRS volatility consistent with the hypothesis, while LIC Housing Finance's

rate sensitivity introduces an alternative source of cyclicality. The hypothesis holds for gold-backed lending but requires refinement to distinguish interest-rate-sensitive secured lending from commodity-backed lending.

VII. STRESS-TESTING RESULTS AND RESILIENCE ANALYSIS

7.1 Comparative Scenario Results

Table 10: Multi-Scenario Stress-Testing Results — CRS Under Base, Expansion, and Recession Scenarios (FY2025)

NBFC	Segment	Base (FY2025)	Good Scenario (Expansion)	Worst Scenario (Recession)	Risk Sensitivity (Worst − Base)
Bajaj Finance	Retail	0.532	0.490	0.618	+0.087
Muthoot Finance	Gold	0.187	0.169	0.217	+0.030
LIC Housing Finance	Housing	0.370	0.337	0.425	+0.056
Shriram Finance	Transport	0.528	0.487	0.608	+0.079

Note: Risk Sensitivity = Worst Scenario CRS − Base (FY2025) CRS. Shock parameters: Credit ±20%, Liquidity ±15%, Market ±15%, Operational ±10% (applied to dimensional scores). Calibrated from RBI FSR and Basel III stress parameters.

7.2 Interpretation of Sensitivity Deltas

The Risk Sensitivity column — the absolute CRS increase from base to worst scenario — provides the most analytically significant output. Bajaj Finance exhibits the highest sensitivity delta (δ = +0.087), indicating that identical macroeconomic shocks produce the greatest aggregate risk escalation in the retail lending segment. The unsecured nature of the retail portfolio means that a 20 percent credit shock translates into full credit loss exposure without collateral recovery. Simultaneously, the worst-case liquidity shock is particularly damaging for wholesale-funded entities without deposit base stability, creating a volatility trap wherein retail NBFCs face compounding credit deterioration and funding cost escalation simultaneously. Under the worst scenario, Bajaj Finance's CRS of 0.618 crosses the high-risk threshold of 0.60.

Shriram Finance's delta (δ = +0.079) reflects the cyclicality of commercial vehicle finance. The worst-case scenario's assumed freight market contraction and rate increase compound to impair borrower cash flows while reducing collateral values — commercial vehicles being depreciating assets whose resale values fall further during downturns when demand for fleet acquisition weakens. Under the worst scenario, Shriram Finance's CRS of 0.608 similarly approaches the high-risk threshold.

Muthoot Finance's delta (δ = +0.030) is the lowest in the sample, confirming the structural resilience of the gold loan model. Even under a 20 percent credit shock, gold's counter-cyclical price behaviour moderates the CRS escalation — rising gold prices during the macro-stress scenario assumed in the worst case improve collateral coverage precisely when credit deterioration is assumed to be most severe. The stressed worst-case CRS of 0.217 remains in the low-risk category (below 0.30).

LIC Housing Finance's delta (δ = +0.056) reflects the stabilising effect of long-duration mortgage collateral on credit risk under stress, partially offset by heightened interest rate sensitivity. The worst-case scenario's assumed rate increases elevate both borrower EMI burdens and funding costs, yet the secured nature of mortgage lending and borrowers' strong repayment prioritisation moderate overall CRS escalation relative to the unsecured segments.

These differential sensitivity outcomes — produced by identical shock parameters uniformly applied —

powerfully confirm that NBFC risk is fundamentally segment-driven. The ratio of worst-to-best sensitivity (δ = 0.087 versus 0.030) is approximately 2.9, indicating that unsecured retail finance absorbs approximately three times more systemic shock than gold-backed lending under identical macroeconomic conditions. This finding has direct implications for regulatory capital calibration: a uniform prudential framework imposing identical requirements across all NBFC segments substantially misallocates regulatory burden.

VIII. DISCUSSION

8.1 Synthesis of Findings

The empirical analysis provides for a number of findings, which are of both academic and policy importance. First, the multi-dimensional CRS framework has proven itself to be a more powerful explanatory tool than single-metric analysis (R^2 = 0.987 versus 0.146, ΔR^2 = 0.841, $p < 0.001$), thus giving statistical support to the theoretical argument that the risk of NBFCs is inherently multi-dimensional and that the monitoring of any single risk category is, at best, foundational and incomplete.

The current study is a direct refutation of the continued relevance of GNPA ratio surveillance as the basis for regulatory or analyst frameworks, as this study illustrates that only 14.6% of the composite risk variation observable can be measured from the GNPA ratio when all four dimensions are monitored at the same time.

Secondly, the Kruskal-Walli's test result (H = 18.615, $p<0.001$, η^2 = 0.434) indicates that 43.4% of the within-panel variance of the CRS is explained by the business model segment membership indicating its importance for the Scale-Based Regulation (SBR) framework of the RBI. SBR divides NBFCs mainly on the basis of size, implying that the size is the most important factor that determines the systemic risk contribution. This study shows that business model is a risk determinant, at least as significant as size, independent of it. A retail NBFC of ₹50,000 crore and a housing finance NBFC of ₹50,000 crore are not the same systemic risk contributors and can only be supervised differently, depending on their structural risk sensitivity.

Third, the correlation between the Retail segment's CRS and the GDP growth is found to be significantly negative ($\rho = -0.624$, $p = 0.040$) while the correlation is positive for Gold segment, which shows that counter-cyclical assets can be used as natural portfolio stabilisers in NBFC sector.

Financial stability policy implications: The regulatory frameworks that, by design, push gold loan NBFCs into restricted limits on LTV or concentration may make the sector's ability to absorb shocks less natural.

Fourth, the stress-testing sensitivity delta analysis gives a quantitative basis for differential regulatory calibration. Given the sensitivity of both retail NBFCs and gold loan NBFCs, the ratio of Retail to Gold sensitivity (δ ratio = 2.9:1) implies that retail NBFCs would need an equivalent systemic risk capital buffer per unit of assets of about 3 times that of gold loan NBFCs. This ratio is quantitative, and can be directly relevant for calibration of the RBI's proposed Counter-Cyclical Capital Buffer (CCyB) for NBFCs.

8.2 Policy Implications

The following are four specific regulatory refinements that are suggested based on the findings. The first is that Segment-Specific Counter-Cyclical Capital Buffers would force Retail and Transport NBFCs to keep a buffer of 1.5 to 2 percent of risk-weighted assets when they are doing well, and release it during a downturn to allow them to keep lending.

Second, LTV-Linked Risk Weight Reduction would provide reduced risk weights for NBFCs with an average portfolio LTV below 60 percent (for gold loans) and below 70 percent (for housing finance), thus incentivizing business models that are structurally robust and have less systemic risk contribution per asset. Thirdly, the framework developed here would enable the regulators to get the monthly NPA calculations and reporting, which would give them 3-6 months warning in advance of the quarterly NPA-based reporting cycle.

Fourth, with ultimate stress realisation deferred, Procyclical Provisioning Requirements for transport finance NBFCs – correlated with Manufacturing PMI and fuel price indices as leading indicators of stress

in the commercial vehicle sector – would front load the buffer accumulation during the boom phase of the freight market.

9. Restrictions and further research.

This study has a few limitations. First, the sample of 4 firms, although representative of the diversity of firms in the segments, is not large enough for generalizing to industry-level patterns.

The results of the Kruskal-Walli's test and regression are internal valid but cannot be generalized to a larger population of around 9400 registered NBFCs without a wider sample. It would be interesting to repeat the exercise for a sample of 30-50 NBFCs at various stages of development, so as to be able to model the panel using fixed effects with controls for firm-level heterogeneity.

Second, the stress testing applies shock uniformly across all segments allowing for controlled cross-segmental comparison but not capturing the differential effects of shocks at the sectoral level.

A shock to fuel prices would impact car finance and not have much impact on gold loans. Indeed, a significant improvement of the stress-testing framework would be to incorporate Monte Carlo simulation using sector-specific shock correlation structures.

Third, the CRS uses constant dimension weights over the course of the study. The significance of risks categories will differ between macroeconomic regimes: During a funding market freeze liquidity risk will be more significant, during an economic recession credit risk will be more significant.

The framework could be improved with dynamic weights based on regime switching models to better respond to shifting risk environments.

Fourth, the governance score and the audit score are both theoretically defensible but are based on a qualitative-to-quantitative proxy. Further studies are needed to create objective governance metrics based on NLP of regulatory filing disclosures or supervisory inspection outcome data.

Fifth, the study does not account for inter-NBFC contagion channels, which are the channels through which stress at one systemically important NBFC spreads to other NBFCs via shared creditors, or wholesale funding markets. The analysis of systemic risk goes well beyond the one entity CRS framework as presented here, and can be greatly improved with bilateral exposure data.

CONCLUSION

This study proposes a Composite Risk Score (CRS) framework for Non-Banking Financial Companies (NBFCs) in India, where each of the five gaps in the existing literature are addressed using a proper PCA-based weight justification process, formal inferential statistical testing and a forward-looking stress simulation process.

The important empirical work is the careful measurement of NBFC risk heterogeneity. In terms of panel regression, the multi-dimensional model is able to explain 98.7% of the variance in CRS compared to the credit-only model, which accounts for only 14.6% of the variance, with an incremental R^2 increase of 0.841, statistically significant at $F(3,39) = 827.71$, $p < 0.001$. The Kruskal-Wallis test with a large effect size ($\eta^2 = 0.434$, $p < 0.001$) shows that the membership of the business model segment is a significant factor determining the risk profile.

The empirical weights derived from PCA weight derivation are similar to those that would be theoretically calibrated, and all six of the alternative specifications of weights show Spearman rank-order correlations $\rho \geq 0.800$ with the base specification.

All seven weight specifications have very similar structural risk hierarchy: Retail (0.527) > Transport (0.361) > Gold (0.342) > Housing (0.287), which shows that the hierarchy is robust. By stress-testing, it is found that unsecured retail finance has on average roughly three times as much systemic shock ($\delta = 0.087$) compared to the gold-backed lending under the same macroeconomic conditions ($\delta = 0.030$), thus a quantitative basis for differential regulatory capital calibration.

With the target of USD 7 trillion economy, the role of NBFC in intermediation of credit will increase. More than a single metric, more than just reactive, the next way for managing this sector is to adopt proactive and multi-dimensional, sensitivity-calibrated risk management. The CRS framework and its statistically validated results offers a practical and scalable basis for this transition – one that recognizes fundamentally different contributions to systemic risk resulting from the collateral-backed versus unsecured lending models and assigns the regulatory burden accordingly.

The empirical analysis establishes several findings of both academic and policy significance. First, the multi-dimensional CRS framework's demonstrated explanatory superiority over single-metric analysis ($R^2 = 0.987$ versus 0.146, $\Delta R^2 = 0.841$, $p < 0.001$) provides rigorous statistical grounding for the theoretical claim that NBFC risk is inherently multidimensional and that isolated monitoring of any single risk category provides fundamentally incomplete characterisation. This finding directly challenges the continued primacy of GNPA ratio surveillance in regulatory and analyst frameworks, which this study demonstrates captures only 14.6% of the composite risk variation observable when all four dimensions are monitored simultaneously.

Second, the Kruskal-Walli's result ($H = 18.615$, $p < 0.001$, $\eta^2 = 0.434$) demonstrating that business model segment membership explains 43.4% of within-panel CRS variance has important implications for the RBI's Scale-Based Regulation (SBR) framework. The SBR classifies NBFCs primarily by asset size, implicitly assuming that size is the primary determinant of systemic risk contribution. This study demonstrates that business model — independently of size — is at least as important a risk determinant. A ₹50,000 crore retail-focused NBFC and a ₹50,000 crore housing finance NBFC are not equivalent systemic risk contributors; they require categorically different supervisory treatment calibrated to their structural risk sensitivity.

Third, the finding that the Retail segment's CRS is significantly negatively correlated with GDP growth ($\rho = -0.624$, $p = 0.040$) while the Gold segment exhibits a positive correlation establishes that counter-cyclical assets can serve as natural portfolio stabilisers within the NBFC sector. This has implications for financial stability policy: regulatory frameworks that inadvertently constrain gold loan NBFCs through blanket LTV restrictions or concentration limits may reduce the sector's natural shock-absorption capacity.

Fourth, the stress-testing sensitivity delta analysis provides a quantitative basis for differential regulatory calibration. The ratio of Retail to Gold sensitivity (δ ratio = 2.9:1) suggests that retail NBFCs require approximately three times the macro-stress capital buffer of gold loan NBFCs to maintain equivalent systemic risk per unit of assets. This quantitative ratio could directly inform the calibration of the RBI's proposed Counter-Cyclical Capital Buffer (CCyB) for NBFCs.

REFERENCES

[1] Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. Journal of Finance, 23(4), 589–609.
[2] Basel Committee on Banking Supervision. (2011). Basel III: A global regulatory framework for more resilient banks and banking systems. Bank for International Settlements.
[3] Basel Committee on Banking Supervision. (2018). Stress testing principles. Bank for International Settlements. https://www.bis.org/bcbs/publ/d450.htm
[4] Bernanke, B. S., & Gertler, M. (1995). Inside the black box: The credit channel of monetary policy transmission. Journal of Economic Perspectives, 9(4), 27–48.
[5] Diamond, D. W., & Dybvig, P. H. (1983). Bank runs, deposit insurance, and liquidity. Journal of Political Economy, 91(3), 401–419.
[6] Dua, P., & Kapur, H. (2018). Macro stress testing and resilience assessment of Indian banking. Journal of Policy Modelling, 40(2), 452–475.
[7] Goswami, G., & Kumar, R. (2022). Performance analysis of NBFCs in India: A comprehensive empirical study. Journal of Emerging Technologies and Innovative Research, 9(6), 248–265.

[8] Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behaviour, agency costs and ownership structure. Journal of Financial Economics, 3(4), 305–360.
[9] Jobst, A. A. (2014). Measuring systemic risk-adjusted liquidity (SRL)—A model approach. Journal of Banking & Finance, 45, 270–287.
[10] Kothari, R., & Sharma, P. (2023). NBFC crisis and regulatory reforms in India: A post-IL&FS analysis. Global Journal of Enterprise Information System, 15(2), 45–62.
[11] Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. Journal of Finance, 29(2), 449–470.
[12] Rajan, R. G. (2010). Fault lines: How hidden fractures still threaten the world economy. Princeton University Press.
[13] Reserve Bank of India. (2019). Liquidity Risk Management Framework for Non-Banking Financial Companies and Core Investment Companies (RBI/2019-20/88).
[14] Reserve Bank of India. (2020). Financial stability report, December 2020. https://www.rbi.org.in
[15] Reserve Bank of India. (2021). Scale Based Regulation (SBR): A revised regulatory framework for NBFCs (RBI/2021-22/112).
[16] Reserve Bank of India. (2023). Financial stability report, December 2023. https://www.rbi.org.in
[17] Reserve Bank of India. (2024). Report on trend and progress of banking in India 2023–24. Mumbai.
[18] Reserve Bank of India. (2025). Financial stability report, December 2025. https://www.rbi.org.in
[19] Sengupta, R., & Vardhan, H. (2020). Non-performing assets in Indian commercial banks: A comparative analysis of public and private sectors. Journal of Asian Economics, 69, Article 101204.
[20] Sinkey, J. F. (2002). Commercial bank financial management (6th ed.). Prentice Hall.
[21] Bajaj Finance Limited. (2015–2025). Annual reports FY 2014-15 to FY 2024-25. https://www.bajajfinserv.in/finance-investor-relations-annual-reports
[22] LIC Housing Finance Limited. (2015–2025). Annual reports FY 2014-15 to FY 2024-25. https://www.lichousing.com/annual_reports.php
[23] Muthoot Finance Limited. (2015–2025). Annual reports FY 2014-15 to FY 2024-25. https://www.muthootfinance.com/annual-reports
[24] Shriram Finance Limited. (2015–2025). Annual reports FY 2014-15 to FY 2024-25. https://www.shriramfinance.in/investors/annual-reports