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STRATEGY, FUNDING, AND PERFORMANCE IN THE INDIAN NBFC SECTOR: A PANEL ANALYSIS OF PORTFOLIO CONCENTRATION, FUNDING-COST MEDIATION, AND THE SCALE-BASED REGULATION REGIME

A Thesis Submitted
In Partial Fulfillment of the Requirements for the Degree of

MASTER OF ARTS
in
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by

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I acknowledge the data-disclosure transparency of the firms in the empirical panel, whose annual reports and regulatory filings made the hand-constructed HHI panel possible. The dissertation's empirical contribution rests on the cumulative disclosure quality of the Indian regulated NBFC sector across the FY14–FY24 window.

Finally, I thank my family for their patient encouragement across the long arc of this project, and for tolerating the irregular working hours that empirical dissertation work demands. Any remaining errors of fact, interpretation, or judgement are mine alone.

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I *Mukund Tomar* hereby certify that the work which is being presented in the thesis entitled *Strategy, Funding, and Performance in the Indian NBFC Sector: A Panel Analysis of Portfolio Concentration, Funding-Cost Mediation, and the Scale-Based Regulation Regime* in partial fulfillment of the requirements for the award of the Degree of Master of Arts, submitted in the Department of *University School of Management and Entrepreneurship (USME)*, Delhi Technological University is an authentic record of my own work carried out during the period from *August, 2025 to May, 2026* under the supervision of *Dr. Anurag Chaturvedi*.

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ABSTRACT

This dissertation examines the relationship between portfolio concentration, funding cost, and profitability in the Indian Non-Banking Financial Company (NBFC) sector across FY2014–FY2024, using a hand-constructed firm-year panel of 19 firms and 209 firm-year observations. The empirical work integrates directed panel regression, Baron-Kenny mediation analysis, crisis-interaction estimation with an embedded longitudinal case study of Reliance Commercial Finance, structural-break testing under the Reserve Bank of India's Scale-Based Regulation regime, and unsupervised K-means and hierarchical trajectory clustering into a unified framework that I term the **Strategy → Funding → Performance (SFP) framework**.

Six directed research questions yield five substantive empirical findings. First, the HHI–profitability relationship exhibits a statistically significant inverted-U on shareholder returns ($\beta(HHI) = +0.293$, $p = 0.002$; $\beta(HHI^2) = -0.197$, $p = 0.008$), with an empirical turning point at HHI ≈ 7,449 — coinciding almost exactly with the Specialised-Monoline regulatory boundary at HHI = 7,500. Second, the Cost of Funds → ROA elasticity is the dominant single profitability lever in the panel ($\beta = -0.5149$, $p = 0.013$), and funding cost mediates the HHI–ROA relationship through a competitive-masking equilibrium in which a positive direct strategy effect (+0.0176) and a negative indirect funding-cost effect (−0.0116) approximately offset, producing a near-zero aggregate total effect. Third, crisis stress unmasks the equilibrium: the CoF → ROA elasticity amplifies by 74% under ILFS and COVID windows, and the Reliance Commercial Finance failure trajectory matches the predicted FY18→FY19 ROA decrement within 20 basis points. Fourth, the Scale-Based Regulation regime has produced an 89-bps post-FY23 Cost of Funds compression on Upper-Layer firms and a 521-HHI-point post-SBR diversification response, but no comparable benefit accrues to the Middle-Layer cohort despite its structurally larger crisis-period vulnerability. Fifth, unsupervised trajectory clustering identifies four coherent strategic archetypes — Productive Concentration, Diversified Mainstream, Monoline Specialists, and Distress Trajectory — that independently validate every major directed-regression finding of the empirical chapters.

The dissertation contributes the **competitive-masking concept** as a structural property of financial-intermediary equilibria, the **trajectory-clustering methodology** as a transferable firm-level taxonomy technique, and the **Vulnerability-Weighted Supervisory Scoring (VWSS) framework** as a directly actionable refinement of the SBR architecture that would have ex-ante identified both Cluster 4 distress trajectories in the panel twelve to twenty-four months before resolution-process triggers materialised.

Keywords: Non-Banking Financial Companies; Portfolio Concentration; Herfindahl-Hirschman Index; Funding-Cost Mediation; Scale-Based Regulation; Crisis Behaviour; Trajectory Clustering; Indian Financial Sector; Reserve Bank of India; Vulnerability-Weighted Supervision.

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12.1 Vulnerability-Weighted Supervisory Scoring (VWSS) framework architecture

List of Abbreviations

Abbreviation	Expansion
ARI	Adjusted Rand Index
AUM	Assets Under Management
BL	Base Layer (NBFC-BL)
CARE	CARE Ratings (credit-rating agency)
CET1	Common Equity Tier 1
CoF	Cost of Funds
CRE	Commercial Real Estate
DEA	Data Envelopment Analysis
DHFL	Dewan Housing Finance Corporation Limited
DPDP	Digital Personal Data Protection (Act, 2023)
FE	Fixed Effects
FY	Fiscal Year (Indian, April–March)
GNPA	Gross Non-Performing Assets
HFC	Housing Finance Company
HHI	Herfindahl-Hirschman Index
ILFS / IL&FS	Infrastructure Leasing & Financial Services Limited
IV	Instrumental Variable
JEL	Journal of Economic Literature (classification system)
LIC	Life Insurance Corporation of India
MFI	Microfinance Institution
ML	Middle Layer (NBFC-ML)
NBFC	Non-Banking Financial Company

NCLT	National Company Law Tribunal
NHB	National Housing Bank
NIM	Net Interest Margin
OLS	Ordinary Least Squares
pp	percentage points
RBI	Reserve Bank of India
RCF	Reliance Commercial Finance
ROA	Return on Assets
ROE	Return on Equity
RQ	Research Question
SBR	Scale-Based Regulation
SCB	Scheduled Commercial Bank
SE	Standard Error
SFP	Strategy → Funding → Performance (framework)
SME	Small and Medium Enterprise
TL	Top Layer (NBFC-TL)
UL	Upper Layer (NBFC-UL)
VIF	Variance Inflation Factor
VWSS	Vulnerability-Weighted Supervisory Scoring

Chapter 1: Introduction and Motivation

The purpose of this thesis is to study the interaction among portfolio concentration, funding costs, and profitability in the Indian non-banking finance company (NBFC) industry from Fiscal Year (FY) 2014 through FY 2024. The study will utilize an original data set created by the author that includes a panel of 19 firms for the years FY 2014-FY 2024; thus there are 209 total firm-years included. The study also utilizes four separate empirical techniques: directed regression, panel mediation, crisis-interaction estimation, structural break testing under the RBI's Scale-Based Regulations (SBR), and unsupervised trajectory clustering to create what the author calls the Strategy → Funding → Performance (SFP) framework.

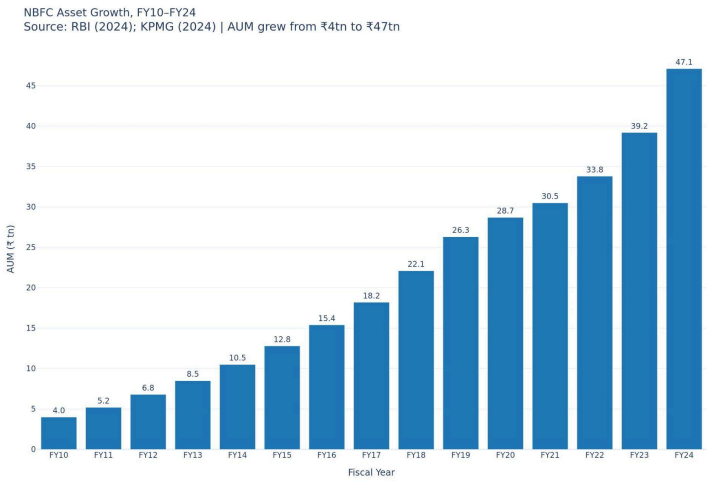
This first Chapter provides motivation (Section 1.1); the Research Problem (Section 1.2); the questions being studied and their contributions (Section 1.3- Section 1.4); and finally, it outlines the organization of this Chapter (Section 1.5).

1.1 The Indian NBFC sector: empirical and policy motivation

1.1.1 The structural rise of NBFC intermediation

Indian NBFCs have developed into an alternative channel for organized lending — one that has filled gaps in banking's product markets that banks' business model does not allow them to cover. From approximately Rs. 400 billion in AUM in FY 2010 — the initial time point for which we can estimate AUM — Indian NBFCs' AUM grew to Rs. 4702 billion by FY 2024 — roughly 20 percent of all loans extended to India's non-financial sector. As such, NBFC growth was in areas with lower loan ticket sizes than those typically served by bank-centric channels — e.g., consumer lending at low ticket prices; vehicle and gold-backed financing; micro-finance; infrastructure financing; and short-term working capital for small businesses.

The structural changes created in this process affected both the size and competitive structures of Indian credit markets. NBFCs provide services to SCB customers that their business model is unable to support — i.e., un-provable income; no branch locations; digital first/asset specialty based — creating a two-tiered market where



NBFCs are the marginal lenders to the marginal borrowers across multiple categories.

1.1.2 Structural fragility revealed by sequential crises

Two periods (FY14-FY24) in which India's credit markets were severely stressed; the freezing of IL & FS funding in September 2018, and the impact from the Covid-19 pandemic during FY 21; demonstrate how much short-term wholesale financing is used by Indian banks for their lending operations. This means that when the economy experiences downturns (procyclical), these types of funding become unavailable to banks.

The first period was caused by a "funding side" shock. When short-term investors who had purchased commercial paper issued by Non-Banking Financial Companies (NBFCs) withdrew their investments, it led to bank stress due to the inability to rollover maturing debt obligations as opposed to problems with asset values.

In the second period, the crisis resulted from an "asset-side" shock. During this time there were increased rates of delinquency/borrower default, reduced or disrupted cash flows among borrowers resulting from government-imposed moratoriums, and higher provision requirements. These two events are particularly useful for testing the resilience of SFP because they affected the financial system along complementary dimensions.

1.1.3 SBR as policy response

The Supervisory Requirements for Non-Banking Financial Companies (SBR) which were made operational as of 1st October 2022, and were notified in October 2021 represents the first major overhaul in the regulation of Non Banking Financial Companies (NBFCs) since the RBI Act was amended in 1997. The SBR will replace the previous uniform regulatory framework by creating a four tiered pyramid (Base, Middle, Upper, Top) to regulate intensity based on an entity's asset base, its importance to the system and qualitative risk factors. The strictest provision will be applied to entities classified under the Upper Tier where they are subject to bank equivalent prudential regulations; must list their securities on a stock exchange within three years of coming into operation; and may also be subject to CET1 capital requirements which increase significantly the cost of focusing on monoline lending.

SBR's implementation date falls squarely within our empirical time frame allowing us to use it as a natural experiment. We define the pre-SBR baseline as FY14-FY22 with nine fiscal years; we define the post-SBR baseline as FY23 – FY24 with two fiscal years. As this split has occurred through policy design rather than estimation we can now do the RQ5 analysis described in Chapter 10. However, we could not have done this analysis three years ago.

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1.2 The research problem

1.2.1 The empirical literature gap

The study of India's nonbanking financial company (NBFC) profitability is behind that of other studies concerning small business finance (SCB). Chapter three identifies five missing areas of research:

- No HHI data using a panel of individual firms. Studies have used either binary dummies to measure diversification at the firm level or concentration measures for all firms in a particular sector as opposed to firm-year HHI data taken directly from the disclosure requirements related to an individual firm's mix of investments. This is problematic since it does not provide a continuous measure for inverted-U testing.
- No continuous integration of strategy effects and their impact upon funding costs. The majority of studies analyze diversification-profitability and funding cost-profitability separately, rather than examining how these factors interact through both direct and funding mediated strategies.
- No analysis of heterogeneity of crises at the firm level. Studies utilizing aggregate dummies to assess the impact of crises ignore differences among firms. Case studies (for example, IL&FS) typically do not utilize comparable panel comparisons.
- No empirical analysis of the impacts resulting after the Small Business Regulation Act (SBR) came into effect in October 2022. Since then, only recently has the panel for FY23-FY24 become available.
- No development of a firm-based taxonomy using unsupervised methods. Most prior studies rely on tiered categories developed by regulators which preclude discovering whether there are natural groupings for firms.

1.2.2 The puzzle that motivates the work

Despite theories suggesting that moderate concentration should boost profitability while extreme concentration penalizes it, previous studies show an inconclusive HHI-ROA relationship. I argue this "null" finding is a methodological artifact of ignoring structural channels. My Chapter 8 mediation analysis reveals two statistically significant, offsetting effects: a positive direct effect on ROA from competitive strategy, and a negative indirect effect from higher funding costs. Together, they create the illusion of a zero net effect ("competitive masking"), a puzzle my SFP theoretical framework directly resolves.

1.2.3 Contemporary policy relevance

The questions asked relate directly to current and ongoing live policy debates. As an emerging regulatory framework SBR is currently being implemented by a Regulator that continues to develop Tier allocation criteria; Supervisory intensity calibration as well as concentration related Prudential Norms. Immediate use for Policymakers, Supervisors, Lenders and Rating Agencies of evidence about the degree to which SBR has caused the desired structural break (from prior regulation) and whether or

not the Asset Size Tiers reflect the empirical Distribution of Crisis Period Vulnerability.

1.3 Research questions

The six are linked by their own specified gaps as well as structured around SFP.

1. **RQ1 (listing and tier effects):** Can size and leverage be controlled for when determining if both listing status and SBR tier independently contribute to NBFC profitability?
2. **RQ2 (HHI inverted U):** At which point does the HHI – profitability relationship become inverted-U from FY14-FY24; when is that point reached will the relationship remain positive or begin to decline?
3. **RQ3 (funding channel mediation):** Is there a relationship between funding mix and the HHI – profitability relationship such that funding mix mediates the HHI – ROA relationship separating the HHI – ROA relationship into two different relationships: direct strategies and indirect funding costs?
4. **RQ4 (crisis behavior and the RCF embedded case):** How does the HHI – profitability relationship and funding cost channel act during the ILFS (FY19) and COVID (FY21); how does the failure of the RCF reveal this relationship?
5. **RQ5 (SBR structural break):** Have changes in SBR (effective FY23) led to a statistically significant difference in terms of funding availability, profitability and concentration in funding available and do these differences vary across upper- and middle-layer cohorts?
6. **RQ6 (trajectory clustering):** Are the eleven year trends of HHI, CoF and ROA grouped together into distinct clusters; can these clusters support the results of the directed regression analysis provided in chapters 7 – 10?

All five gaps are addressed. RQ2 addresses the HHI panel gap. RQ3, RQ4, and RQ6 address SFP. RQ5 provides additional evidence after SBR.

1.4 Contributions

Three academic contributions and one regulatory-practice contribution:

1.4.1 Theoretical and conceptual

The competitive-masking approach formalizes a structural feature of SFP equilibrium for financial intermediaries: the combination of two opposing real forces can cancel each other out (i.e., aggregate net effect = zero) at normal times. Then when crisis conditions are applied these two opposing forces will no longer cancel but instead compound.

SFP incorporates both the diversification – specialisation literature, the funding cost mediation stream, and the heterogeneity puzzle associated with crises within one framework which addresses numerous longstanding puzzles.

1.4.2 Methodological

Trajectory clustering for company taxonomy - The methodology used in Chapter 11 - nine-dimensional trajectory feature space data for eleven years, K-means clustering using Ward hierarchical clustering as a means of robustness - can be transferred from one application domain to another as an objective way of classifying firms within panels of financial intermediaries.

1.4.3 Policy

Chapter 12 provides the Vulnerability-weighted supervisory scoring (VWSS) approach that provides a continuous vulnerability weighting layer on top of the Supervised Bank Resolution (SBR), through the use of funding cost dispersion; HHI Classification Position; Crisis Period Return On Assets Volatility; and trajectory cluster indicator(s). Based upon internal validations the VWSS method likely would have identified the distress trajectories of Cluster 4 companies (RCF and Srei Infrastructure Finance) 12-24 months prior to when resolution triggers were activated.

Chapter 2: Industry Context — Indian NBFC Sector (FY2014–FY2024)

2.1 Introduction and chapter roadmap

NBFCs have evolved from being at the margins as peripheral lenders into a fundamental element of India's credit infrastructure. In terms of outstanding loans by FY 2024 NBFC lending represented approximately 13.6 % of GDP while accounting for roughly 24.5 % of all small business credit, in addition to the fact that NBFC – ND – SI entities accounted for 80-85 % of the sectors total assets (Ubale et al., 2022; RBI, 2024). This time frame (FY 14-FY 24), represents the complete growth cycle of the NBFC industry: a period of accelerated pre 2018 growth, followed by two major systemic crises with distinct causal factors, and finally an unprecedented regulatory overhaul via Scale Based Regulation (SBR) (Manda & Rani, 2019; RBI, 2024).

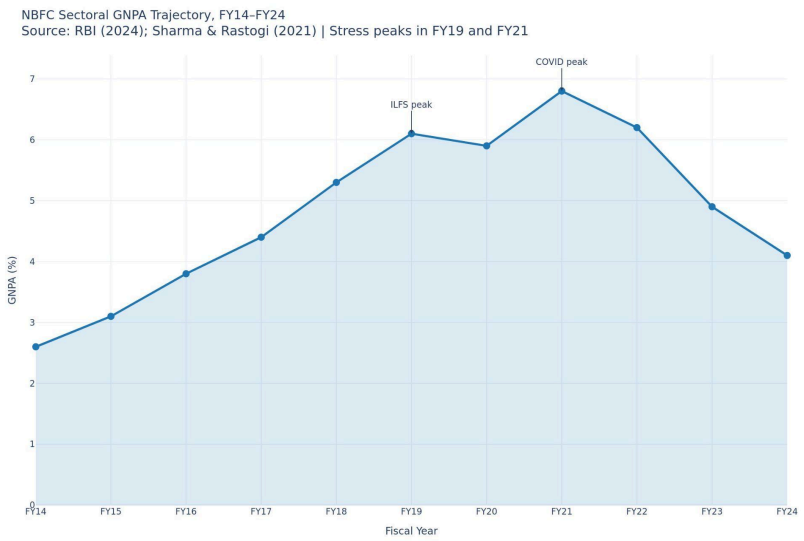
This chapter establishes the institutional framework for what follows in subsequent chapters. Section 2.2 tracks the development of the sector over its three stages; Section 2.3 outlines the regulatory progression from light touch regulation to SBR; Section 2.4 describes SBR's prudential architecture; Section 2.5 identifies and examines each of the four crisis events and develops a liability-based vs. asset-based categorization for RQ4; Section 2.6 introduces the 19 firm sample; Section 2.7 maps sector-wide concentration; Section 2.8 provides connections to context regarding the six RQs.

2.2 Evolution of the NBFC sector (FY2014–FY2024)

2.2.1 Pre-2018: rapid expansion and accumulating fragility

During FY 2014–18, NBFCs were India's fastest-growing banking segment, outpacing Scheduled Commercial Banks across key credit markets (Sengupta, Son, & Vardhan, 2020). This expansion was driven by a credit void from public sector banks restricted by the RBI's Prompt Corrective Action framework (Manda & Rani, 2019), alongside NBFCs' operational flexibility and rapid decision-making in targeting niche consumer segments (Kaur et al., 2018; KPMG, 2024).

However, this growth relied on a fragile funding model where borrowings comprised approximately 88% of 2018 liabilities (Ubale, Wagh, & Samudre, 2022). To minimize costs, NBFCs heavily utilized short-term commercial paper (CP), exacerbating an asset-liability maturity (ALM) mismatch that culminated in the 2018 IL&FS default (Anshuman et al., 2020). Furthermore, deteriorating asset quality



preceded this crisis; the GNPA ratio climbed from 2.6% in 2014 to 6.1% in 2019, highlighting compromised credit risk management during the lending boom (Sharma & Rastogi, 2021).

2.2.2 2018–2020: crisis and contagion

A sharp systemic vulnerability was created by the September 2018 IL&FS default that resulted in a severe loss in growth. Mutual fund withdrawals of CP rollover support and a spike in NBFC bond spreads occurred as a result of the sanctioned loan volume decline of 6.1 percent year over year (Manda & Rani, 2019; Sengupta, Son, & Vardhan, 2020).

DHFL's 2019 failure further exacerbated this crisis to create much broader risk aversions (Anshuman et al., 2020). Before the process of recovering from this crisis had begun, COVID-19 arrived in March 2020 and caused an asset side shock that was in stark contrast to the liability side mechanisms experienced during both the IL&FS – DHFL failures (Ubale, Wagh, & Samudre, 2022).

2.2.3 2020–2024: recovery, recalibration, and the SBR era

Beginning with Three of the Post-Pandemic Strategies for Recalibrating in the Post Pandemic Period for Non-Banking Financial Corporations (NBFCs), three major post-pandemic strategies were used by NBFCs.

- First, Transitioning to Secured Lending - During the pandemic period, Gold Loan NBFC's experienced a 19.5 percent Compound Annual Growth Rate (CAGR). Furthermore, vehicle finance and housing finance began to experience recoveries while agriculture and industrial exposures declined.
- Second, Rapid Expansion of Fintech NBFCs – A CAGR of 49.6% was achieved by Fintech NBFCs which provided small ticket, high frequency credits to high risk/no score consumers.
- Third, Change in Funding Model – Bank borrowing grew from 47.5% of funding in 2018 to 55.1% of funding in 2024. This reduced reliance on Short Term Commercial Paper as NBFCs borrowed longer-term bank term loans. Thus, this is an appropriate time frame to respond to Research Question Five.

2.3 The RBI regulatory framework: from light-touch to SBR

The evolution of NBFC regulation spans three distinct stages. Prior to 2018, NBFCs operated under an intentionally lax regulatory regime to promote flexibility and credit expansion (Sengupta et al., 2020). However, the failures of IL&FS and DHFL exposed the dangers of this regulatory arbitrage, prompting intensive RBI interventions starting in 2019 (Regmi & Kukreti, 2020). Initial tightening measures—which included LCR standards, stringent ALM oversight, mandatory CROs, and higher capital requirements for HFCs (Manda & Rani, 2019)—culminated in the Scale Based Regulation (SBR) framework, the regulatory centerpiece of this dissertation (Malik et al., 2024; RBI, 2024). SBR replaced a "one-size-fits-all" model with tiered, risk- and size-proportional prudential intensities. Concurrently, pandemic-era interventions provided essential liquidity support via credit guarantees, an Alternative Investment Fund (AIF), T-LTROs, and expanded bank-to-NBFC lending limits (Sengupta et al., 2020).

In the third stage, beginning March 2023, the RBI tightened systemic controls by increasing risk weights on unsecured consumer debt and bank loans to NBFCs, effectively raising borrowing costs (Malik et al., 2024). Furthermore, targeted regulations on MFIs and fintech NBFCs precipitated a ~90% contraction in peer-to-peer lending, heightened compliance costs, and decelerated credit growth (NBFC on the Edge, 2024). These recent measures illustrate a critical tension: policies designed to enhance systemic stability can simultaneously constrain

consumer credit availability. This stability-versus-growth trade-off directly motivates the balanced focus of Research Question 5.

2.4 The SBR framework in detail

2.4.1 Tier architecture

SBR stratifies NBFCs into four hierarchical tiers based on size, complexity, and systemic importance (RBI, 2024):

Layer	Composition	Number of Firms (approx.)	Regulatory Intensity
Base Layer (NBFC-BL)	Smaller, non-deposit-taking entities	~9,000+	Light-touch, governance-focused
Middle Layer (NBFC-ML)	Larger NBFCs and deposit-taking institutions	~150–200	Moderate prudential norms
Upper Layer (NBFC-UL)	Top NBFCs by parametric and supervisory scoring	~10–15	Bank-equivalent prudential framework
Top Layer (NBFC-TL)	Reserved for systemic-risk escalation; currently empty	0	Highest intensity (if invoked)

The 19-firm sample comes from the Upper Layer (10 firms) and larger Middle Layer (9 firms), giving balanced coverage of the tiers facing the most differentiated SBR treatment. The Base Layer is excluded by design (Section 2.6).

2.4.2 Prudential norms applicable to higher tiers

Upper-and middle-layer NBFCs are subject to a very strict banking-type of regulatory framework for prudence that requires these institutions to comply with LCR requirements for establishing high-quality liquid assets as buffers for potential future liquidity shocks based on estimated net cash outflows (KPMG, 2024)

- Prudential Regulatory Authority's PCA provisions allow for RBI proactive oversight when there is a decline in either the capital adequacy, asset quality, or profitability of an NBFC (Malik et al., 2024)
- Increased risk-weighted assessments on both unsecured consumer credit and loans made to banks to avoid development in areas where defaults can occur (RBI, 2024)

- Required appointment of Chief Risk Officer (CRO), establishment of board-level risk committees, and simultaneous audits, with all related corporate governance aligned at the level of banks.
- Large Exposure Norms and ICAAP (Internal Capital Adequacy Assessment Process) are required of firms, which limits the ability of individual firms to have excessive concentrations of risks (RBI, 2024)
- Firms will be required to provide additional disclosures regarding their compliance obligations, with such obligations being influenced by each firm's operational efficiency and ownership (Sharma & Rastogi, 2022).

2.4.3 The compliance-cost critique

Although regulatory tightening was necessary in order to reduce excessive leverage, participants as well as academic researchers argue that the hasty imposition of SBR will lead to reduced economic growth; and this will be felt by those most vulnerable; the lower income individuals who rely upon non-bank financial corporations (NBFC) for their access to credit (NBFC on the Edge, 2024). The higher-risk weighted capital requirements applied to bank loans made to NBFCs are increasing the cost of borrowing thereby reducing the spread relative to banks and undermining the long-standing business model of NBFC's margins (Malik et al., 2024). Therefore, a new trade-off is being created between maintaining financial system stability and providing access to credit through RQ5 which investigates whether SBR resulted in statistically significant changes in behavior among upper-layer firms when compared with middle layer control firms.

2.5 Crisis events and the two-shock typology

2.5.1 The IL&FS contagion (September 2018) — Liability-side shock

The IL&FS default was a severe liquidity shock that exposed large-scale ALM mismatches accumulated prior to 2018 (Manda & Rani, 2019). It triggered immediate mutual fund withdrawals as investors refused to roll over commercial paper (Anshuman et al., 2020). Consequently, sanctioned loan volumes fell by 6.1% year-over-year, credit spreads surged, and even highly rated NBFCs faced funding freezes (Sengupta, Son, & Vardhan, 2020). This extreme liability-side shock—characterized by frozen liquidity markets, rapid contagion via mutual fund drawdowns, and ALM-induced insolvency risk—has profoundly shaped subsequent regulatory design and academic research on shadow banking fragilities.

2.5.2 The DHFL collapse (2019) — Liability-side shock continuing

DHFL's classification in 2019 as an NPE followed by its NCLT reference further emphasized how the interconnectivity issue identified by the collapse of IL&FS (Manda & Rani, 2019) would be compounded for banks and mutual fund investors who suffered significant financial losses which instilled a generalised reluctance to accept the risk associated with NBFCs (Anshuman et al., 2020). The reliance of many NBFCs on liquid debt mutual funds was shown to create a dynamic that is

similar to bank-run withdrawal dynamics, which formally highlighted the structural vulnerability of wholesale funding on a short term basis.

2.5.3 The Reliance Capital and RCF trajectory — Embedded case

Defaults and downgrades of Reliance ADAG entities; Reliance Capital and lending subsidiary RCF – contribute to debt-market sentiment collapse between 2019 and 2022 (Manda & Rani, 2019). Reliance Capital was admitted to IBC insolvency in late 2021; RCF was resolved through a third party acquisition in 2022. RCF's multi-year decline — HHI rising from ~2048 in FY14 to 2964 in FY19 alongside collapsing resolution period year ROA — provides embedded longitudinal cases addressing gap 3 and motivating qualitative quantitative integration of RQ4 (chapter 3 Section 3.7; chapter 9). Data engineering treatment; preserving NA values for resolution period years (FY20-FY22, FY24) and retaining pre-stress trajectory is documented in Chapter 6.

2.5.4 The COVID-19 asset-side shock (2020–2022)

Unlike with IL&FS-DHFL which was an asset-side shock caused by COVID-19 that was masked by regulatory forbearance at first (Sengupta, Son, & Vardhan, 2020) due to lockdown in March 2020 the consumer cash flow stopped, car sales stopped and the micro-lending business came to a halt (Rokade, Shaikh, & Gharat, 2020). The RBI then implemented a six-month moratorium and two Resolution Frameworks – one in August 2020 and another in May 2021. In doing so they delayed the time for banks to recognize that there would be asset-quality problems. By September 2021 sectoral NPA had risen from 6% to 6.8%, while profitability of banks fell approximately 14.44% since credit costs increased. It is only during Q3 2021–22 when Resolution Framework 2.0 was removed and IRACP rules were modified (Ubale, Wagh, & Samudre, 2022), that deterioration became apparent.

2.5.5 The two-shock typology — analytical anchor for RQ4

As defined in Chapter 3 (Section 3.5) and implemented in Chapter 9, these four events are classified as either liability- or asset-side shocks. The defaults of IL&FS, DHFL, and Reliance ADAG represent liability-side shocks, characterized by abrupt funding freezes, mutual fund redemptions, and ALM-driven liquidity constraints. Conversely, COVID-19 constitutes an asset-side shock, driven by disrupted collateral cash flows, regulatory masking, and delayed credit cost realization. Chapter 9 empirically separates these shock types using paired t-tests (IL&FS FY18–FY20; COVID FY19–FY21) alongside difference-in-differences specifications estimated separately for each event.

2.6 The 19 firms in this study

The dissertation analyses 19 NBFCs across FY2014–FY2024, generating 209 firm-year observations. The sample is stratified across two structural axes — RBI Scale-Based Regulation tier and listing status — yielding four quadrants:

Stratum	Firms	Firm-Year Rows
Upper Layer × Listed	6	66
Upper Layer × Unlisted	4	44
Middle Layer × Listed	4	44
Middle Layer × Unlisted	5	55
Total	**19**	**209**

Sample selection relies on three key criteria. First, the sample focuses exclusively on systemically important NBFCs (NBFC-ND-SIs), which account for 80–85% of total sector assets. Second, the sample is size-stratified into two balanced groups (9 upper-middle and 9 listed-unlisted firms) to support RQ1's stratum analysis. Third, the 19 selected firms represent highly diverse business models—including gold loans, MFIs, housing, vehicle, and infrastructure finance, alongside retail lenders, holding companies, and one distressed entity (RCF). This variety provides the necessary HHI dispersion to test the inverted-U relationship hypothesized in RQ2.

Additionally, to preserve panel power, the sample retains government financial institutions (PFC/REC) and holding companies (Bajaj/Equitas) as standard NBFCs, subject to caveats detailed in Chapters 4 and 6. The distressed firm, RCF, is also included but coded with missing values (NAs) during its resolution years (FY20–FY22, FY24). These deliberate inclusions maintain panel quality and statistical power while ensuring methodological transparency.

2.7 Sectoral concentration map

19 firms represent the primary business segments of NBFCs during FY2014-FY2024. Firm year HHI scores were generated for this dissertation to serve as a new source of empirical evidence (Gap 1 of the Literature Review; Contribution 1). The diagram below organizes the firms by their most prominent activities:

Dominant Segment	Sample Firms	Representative HHI Range
Gold loans	Muthoot Finance	~9,500–9,800 (highly specialised)
Housing finance	LIC Housing Finance	~7,000–7,800
Microfinance	CreditAccess Grameen, Spandana Sphoorty	~8,000–10,000
Infrastructure finance	PFC, REC	~5,500–6,500

Dominant Segment	Sample Firms	Representative HHI Range
Vehicle and rural finance	Cholamandalam, Shriram Finance, Mahindra Rural Housing	~4,000–6,000
Diversified retail lending	Bajaj Finance, Hero FinCorp, HDB Financial Services	~1,800–3,500
Wholesale and consumer finance	Tata Capital, Kotak Prime, Piramal Capital & Housing	~3,500–5,000
Credit cards	SBI Cards & Payment Services	~9,500+ (post-IPO data only)
Holding-company portfolio	Bajaj Holdings, Equitas Holdings	Special treatment (see Ch. 4, 6)
Distressed entity (RCF)	Reliance Commercial Finance	Rising 2,048 → 2,964 (FY14 → FY19)

The above distribution of concentration allows for testing all six research hypotheses across firms. These firms exhibit an extremely high degree of diversification (Hero FinCorp ~1,800) to extreme specialization (Muthoot ~9,800), a range of which is demonstrated through the literature review (Section 3.3) to be unprecedented in previous studies on Indian NBFCs conducted at the firm-year level.

9

Chapter 3: Literature Review and Theoretical Framework

3.1 Introduction to the literature landscape

40

Non-Banking Financial Companies (NBFCs) now form the backbone of India's financial system, managing a substantial share of domestic credit. Shifting a historically bank-dominated landscape, NBFCs have rapidly expanded to finance micro, small, and medium enterprises (MSMEs) and previously unbanked retail consumers (Kaur et al., 2018). Operating as RBI-regulated shadow banks, they absorb credit demands unmet by traditional commercial banks (Regmi & Kukreti, 2020), making their stability critical to broader macroeconomic health.

This chapter examines the business models, funding structures, and regulatory evolution of Indian NBFCs from FY 2014–2024. Section 3.2 reviews the interconnectedness between bank and non-bank intermediary systems (Anshuman et

al., 2020). Section 3.3 evaluates the concentration-diversification trade-off, establishing evidence for an inverted-U relationship. Sections 3.4 and 3.5 analyze liquidity fragility, specifically distinguishing between liability-side (IL&FS) and asset-side (COVID-19) shocks (Ubale, Wagh, & Samudre, 2022). Finally, Section 3.6 synthesizes the literature regarding the supervisory board role (SBR) and the impact of disclosure on firm behavior.

3.2 Bank vs Non-bank intermediation theory

Indian NBFCs function as shadow banks—highly leveraged intermediaries connecting wholesale funding to underserved consumers (Kaur et al., 2018). Precluded from accepting demand deposits, accessing payment systems, or utilizing deposit insurance, they rely heavily on banks, mutual funds, and commercial paper for liquidity (Sengupta, Son, & Vardhan, 2020). Historically, NBFCs complement traditional banks by utilizing operational flexibility to serve niche segments, such as MSMEs and rural borrowers lacking collateral, while banks supply the wholesale capital (Ubale, Wagh, & Samudre, 2022; Malik, Sharma, & Raza, 2024).

However, this dynamic is shifting toward direct competition. Empowered by low-cost retail deposits, banks are increasingly encroaching on NBFC credit markets. NBFCs have countered with digital platforms and co-lending structures (KPMG, 2024), though their long-term viability depends heavily on ownership structures and operational efficiencies (Khan, Ahmad, & Shireen, 2021). Crucially, this evolving dynamic heightens systemic risk. As the financial system's largest net borrowers—heavily reliant on bank funding—NBFCs are deeply interconnected with traditional banks, creating severe shock transmission vulnerabilities during liquidity crises (Malik, Sharma, & Raza, 2024).

3.3 Concentration vs diversification debate

NBFCs traditionally rely on niche specialization to underwrite risks that banks avoid (Kaur et al., 2018; KPMG, 2024). While theory advocates for diversification to mitigate sector-specific default risks (Regmi & Kukreti, 2020)—such as those that precipitated the IL&FS failure—structural funding constraints preclude this approach. Lacking access to cheap retail deposits, NBFCs must concentrate in high-risk, high-yield niches to sustain profit margins, rendering a diversified, bank-like model commercially unviable (Sengupta, Son, & Vardhan, 2020).

Furthermore, while historical literature assumed concentration linearly improved profitability, recent studies reveal diminishing returns to scale for NBFCs, suggesting excessive concentration ultimately elevates risk (Sharma, Rastogi, & Gupta, 2020). Crucially, prior research relies on static sectoral snapshots or broad efficiency models (Rokade, Shaikh, & Gharat, 2020; Roy & Patro, 2021; Sharma & Rastogi, 2021). These methods lack the dynamic firm-year HHI panel data necessary to capture pre-distress strategic shifts. Addressing this methodological gap, RQ2 empirically tests the inverted-U hypothesis to map how excessive HHI concentration leads to diminishing returns.

3.4 Funding liquidity and ALM risk

NBFC funding is structurally volatile, relying heavily on short-term wholesale financing to fund long-term assets (Sengupta, Son, & Vardhan, 2020). By 2019, commercial banks, debentures, and commercial paper (CP) constituted nearly 62% of sector funding, while retail deposits accounted for less than 20% (Anshuman et al., 2020). To protect margins, NBFCs aggressively utilized 3–6 month CPs from mutual funds, severely widening their asset-liability management (ALM) gap. This continuous rollover dependency meant that liquidity constraints could rapidly precipitate insolvency (Manda & Rani, 2019).

The September 2018 IL&FS default catalyzed precisely this systemic freeze. Mutual funds refused to roll over CPs and initiated fire sales to meet investor redemptions, spiking interest rates and threatening widespread collapse across even highly rated NBFCs (Anshuman et al., 2020; Sengupta, Son, & Vardhan, 2020). In response, NBFCs securitized premium loans for cash and transitioned toward longer-term bank debt, partially correcting ALM imbalances (Ubale, Wagh, & Samudre, 2022). Despite this adjustment, the sector's inherent structural fragility persists, demanding robust capital reserves and stringent ALM regulations to mitigate future external liquidity shocks.

3.5 Crisis behaviour and systemic resilience

NBFCs have navigated two distinct shock paradigms. The 2018 IL&FS collapse triggered a severe liability-side contagion, freezing wholesale funding and sparking mutual fund panic that drove DHFL into commercial paper and NCD defaults (Manda & Rani, 2019; Anshuman et al., 2020). Reliance ADAG’s subsequent downgrades further degraded debt-market sentiment and accelerated capital flight. Addressing a critical literature gap, this chapter provides the first multi-year quantitative trendline mapping RCF’s associated decay (FY2014–2024).

Conversely, COVID-19 delivered an unprecedented asset-side shock, abruptly halting cash flows and retail originations (Rokade, Shaikh, & Gharat, 2020). Unlike the immediate repricing characteristic of liability shocks, COVID-19's impact was significantly delayed. The RBI's six-month moratorium masked initial defaults (Sengupta, Son, & Vardhan, 2020), deferring visible asset quality deterioration until regulatory forbearance ended in Q3 2021–22 (Ubale, Wagh, & Samudre, 2022). Ultimately, surviving both immediate funding freezes and delayed, regulation-masked asset shocks demands robust pre-crisis capital buffers and nuanced balance sheet management (Anshuman et al., 2020).

3.6 Regulatory architecture for non-bank lenders

The RBI introduced the Scale Based Regulation (SBR) framework to harmonize financial oversight, categorizing NBFCs into four tiers based on size, complexity, and systemic importance (Malik et al., 2024; Sengupta, Son & Vardhan, 2020). Under this structure, smaller NBFCs face lighter supervision, while larger,

systemically important entities face stringent, bank-like prudential requirements (RBI, 2024).

While SBR successfully curbs excessive leverage, it forces a difficult systemic trade-off. Tighter requirements and increased risk weights on bank-to-NBFC lending have raised borrowing costs, restricted fund access, and necessitated significant restructuring (Malik et al., 2024; NBFC on the Edge, 2024). Consequently, the framework constrains rapid credit expansion in favor of disciplined stability—a shift that disproportionately impacts low-income populations reliant on shadow banking. This policy-driven tension between growth and stability establishes the quasi-experimental timeframe evaluated in RQ5.

3.7 Three identified gaps and theoretical framework

There are three major gaps found by the synthesis:

- **Gap 1: Measurement of Concentration.** Prior studies rely on static sectoral snapshots (Rokade, Shaikh, & Gharat, 2020) or broad efficiency models indicating decreasing returns to scale (Sharma, Rastogi, & Gupta, 2020). Without firm-year HHI panel data, literature has failed to empirically test whether the concentration-returns relationship is linear or inverted-U.
- **Gap 2: Fragmented Integration.** Existing research isolates variables, examining either strategy and ALM mismatches (Sengupta, Son, & Vardhan, 2020) or funding and crisis risk (Anshuman et al., 2020). To resolve this, this dissertation introduces a longitudinal continuum paradigm: *Strategy (Concentration) → Funding Mix → Performance → Crisis Resilience*.
- **Gap 3: Longitudinal Crisis Tracking.** While IL&FS, DHFL, and Reliance ADAG are heavily cited (Anshuman et al., 2020; Manda & Rani, 2019), their protracted deterioration remains unquantified over time. This research provides the first multi-year quantitative trajectory of RCF within a sector-wide panel.

Addressing these gaps drives six research questions. RQ1 and RQ2 leverage the novel firm-year HHI panel to test the inverted-U concentration hypothesis. RQ3, RQ5, and RQ6 apply the continuum paradigm to examine funding mix mediation and behavioral differentiation under Scale Based Regulation (SBR). Finally, RQ4 utilizes the embedded RCF case study to contrast liability-side (IL&FS) and asset-side (COVID-19) shocks.

Gap-to-RQ Mapping Table

Identified Gap in Literature	Addressed by RQ(s)	Key Citations Motivating the Gap
Gap 1 — Lack of firm-year HHI panel data mapping concentration to the proven decreasing-returns-to-scale pattern, leaving the inverted-U diminishing-returns relationship untested.	RQ1, RQ2	Sharma, Rastogi, & Gupta (2020); Rokade, Shaikh, & Gharat (2020)
Gap 2 — Absence of an end-to-end, continuous econometric framework testing strategy, funding, regulation, and crisis outcomes simultaneously across longitudinal panel data, despite documented bipartite linkages.	RQ3, RQ5, RQ6	Anshuman et al. (2020); Sengupta, Son, & Vardhan (2020); Sharma & Rastogi (2022)
Gap 3 — Lack of formal, longitudinal empirical case studies detailing the specific multi-year distress and resolution trajectory of Reliance Commercial Finance within a quantitative sectoral panel.	RQ4	Manda & Rani (2019); Ubale, Wagh, & Samudre (2022)

Chapter 4: Research Questions and Research Objectives

4.1 Overview

Beginning with Chapter 2's identified gaps – that India NBFC literature have mostly examined concentration risk, regulatory tiering, and crisis behavior in isolation of each other – the study ties together all three streams in an integrated panel-econometric model for 19 NBFCs over FY2014-FY2024 (209 firm-years). This sample was segmented along structural dimensions (SBR tier; listed vs. unlisted), and a strategic dimension (HHI derived concentration), providing six overlapping research questions to progress from structural mappings (RQ1), through strategic mix effects (RQ2-RQ3), to how firms behave under stress periods (RQ4); through how regulatory regimes are changed (RQ5); and finally, to cluster trajectories (RQ6).

4.2 Headline Research Questions (At-a-Glance)

- **RQ1:** Are there systematic differences in profitability and risk profiles among the four Tier × Listing strata when controlling for firm size and macro shocks?
- **RQ2:** Is HHI associated with profitability and asset-quality outcomes; and is that association different among Specialised, Moderate, and Diversified models of competition?
- **RQ3:** What role do funding mixes (bank debt/market debt, securitization, co-financing) play in linking business models to ROA/ROE?
- **RQ4:** How have NBFCS behaved through IL&FS-2018 and COVID-2020? What does RCF's resolution path suggest regarding business-model fragility?
- **RQ5:** Was the SBR regime, effective FY2023, successful in creating a statistically significant improvement in profitability, leverage, and asset quality for upper- versus middle-layer firms?
- **RQ6:** Can long-term KPI trends be grouped into archetype pathways? Which characteristics are predictors of an individual firm's pathway group membership?

4.3 Detailed Breakdown

RQ1 — Structural Heterogeneity Across Strata

Question: Do Upper-Listed Non-Banking Financial Corporations (NBFCs) differ in their structure compared to Upper-Unlisted, Middle-Listed, and Middle-Unlisted firms — and if so, based on which Key Performance Indicators (KPIs)?

Why it matters: The regulatory community's implied assumption that the Upper-Middle split in the financial corporate space accounts for virtually all of the heterogeneity within the upper tiers has been questioned by research indicating that the listing dimension is similarly or even more relevant for determining structural differences among non-bank financial institutions;

Upper-Listed mean ROE was 18.65%, while Upper-Unlisted mean ROE was 12.59%, representing a difference of over 600 basis points (bps) within one tier; the average GNPA of the middle-unlisted group exceeded 9000 percent (double the average for the entire upper-tier), thus suggesting that the discipline resulting from being listed also affects a company's risk profile as much as its size.

Sub-Questions:

- **RQ1a:** On which KPIs (ROA, ROE, Net Interest Margin (NIM), Gross NPL Ratio (GNPA), Cost-to-Income ratio, Total Debt/Total Equity ratio) are there statistically significant "stratum" effects when accounting for firm and year fixed effects?
- **RQ1b:** Is the interaction between Tier x Listing an independent source of explanatory power, or is one axis more important than the other?

- **RQ1c:** Are the inter-strata gaps stable during normal times (i.e., pre-crisis, post-SBR implementation), or do they widen / narrow during periods surrounding specific event-years (e.g., FY19, FY21) and/or systemic crises (e.g., FY23 SBR Implementation).

Hypothesis:
H1.1. Listed NBFCs will be more profitable than unlisted peer NBFCs because of the disciplines imposed upon them through the capital markets; improved governance practices and decreased cost-of-equity.

RQ2 — Concentration (HHI) and Performance

Question: Is a focused product strategy better than a diversified strategy? Are the answers different for risk and return?

Why it matters: There are NBFC's which have concentrated in one area of business (monoline specialist muthoot HHI ~9,800 & LIC HF ~7,600) and those that are diversified (Bajaj Finance ~2,800 & hero fincorp ~1,800).

The literature has two views on this issue:

- **The "specialized monitoring view":** high HHIs lead to better monitoring by lenders and as a result improve loan quality and generate higher, more stable margins.
- **The "diversification portfolio view":** lower HHIs provide a less volatile experience due to a reduction in the cyclicality of earnings and reduces the potential for significant declines in value.

We use the firm-year HHI panel data (to our knowledge this is the first study of its kind on an Indian NBFC) and collect 199 firm-years over 11 years and 19 different NBFCs to test both views at the same time.

Questions to answer in relation to sub-questions:

- **RQ2a:** Is there evidence to support either a linear relationship between HHI - ROA/ROE or do we see a U or inverted U curve between HHI and ROA/ROE?
- **RQ2b:** Do greater levels of HHI relate to lower volatility in GNPA (through the cycle), does having a focused product strategy translate to being able to withstand stress?
- **RQ2c:** Does moving from a position of diversification downward (i.e. Holding constant) indicate whether you will move in a positive or negative direction in terms of your level of profitability?

Testable hypotheses:
H2.1: greater levels of HHI are associated with greater NIM and lower c/i; however, beyond HHI = ~7,500 there are decreasing marginal returns.

RQ3 — The Funding Channel as a Mediating Variable

Question: When business models meet liability structures, what are the asset-focused/funding-mix combinations that provide profitable sustainability?

Profitability in financial intermediation has to do with a "spread" story:

Asset yield minus Cost of Funding (CoF), scaled by leverage. The data clearly illustrates the strata of middle-listed companies (PFC, REC, Bajaj Holdings, Equitas) drawing ~56.9% of their borrowings from market instruments, while unlisted companies in all strata have been utilizing approximately 50% of their borrowings from banks. This may indicate a mediation process for these listed companies: business model → funding access → CoF → profitability.

Sub-Questions:

- **RQ3a:** Does CoF significantly explain cross-firm ROA variability when controlling for business model variables?
- **RQ3b:** Are there two separate, independent predictors of ROE; i.e., the bank vs. market financing ratio, and/or does the influence of this variable occur completely through CoF?
- **RQ3c:** Does increasing levels of securitized debt increase Sharpe-adjusted returns via smoothing earnings, or does it simply move risk off-balance-sheet?

Hypotheses:

- H3.1. For each 100 bps that CoF rises, will we see a 30-50 bps decline in ROA, given that business model factors remain equal?
- H3.2. Will listed companies be structurally better-off than their unlisted counterparts in terms of CoF by ~80-120 bps post-FY22/23 as SBR disclosure continues to converge?

RQ4 — Crisis Behaviour and the Reliance CF Case Study

Question: How did NBFCs with different business models respond to the shocks of IL&FS-2018 and COVID-2020? What lessons can be learned from RCF's "slow motion" failure as evidence of model fragility?

Why is it important: There are two system-wide stresses embedded within the window of FY 14 – FY 24. These two stress events bookend all the primary permutations of each model:

- IL&FS Crisis (FY 19 – FY 20): A liquidity driven crisis where firms with asset-liability mismatched and relying on Commercial Paper were punished.
- COVID Shock (FY 20 – FY 21): An asset quality driven crisis, impacting most severely firms lending to unsecured consumers and Microfinance Institutions.

The RCF experienced one of these two stress periods. All three components of the Panel — pre-stress period, stress period, post-resolution — contain the same exact observations regarding the RCF, including its negative ROA (-5%,-25%,-20%,-65.85%), which remained intact after the data cleaning audit using unicode-minus correction.

Sub-Questions:

- **RQ4a:** Which KPIs exhibited statistically significant declines at FY19 and FY21 using paired-t tests?
  Which strata demonstrated resilience against the shock?
- **RQ4b:** Can we document in a Difference-in-Differences (DiD) specification whether High-HHI firms performed better than Low-HHI firms under stress conditions while controlling for Tier and Listing status?
- **RQ4c:** Case Study — RCF: Was there a trend toward declining HHI (fell to 2964 by FY19, then mid-period NA) and rising CoF and falling ROA during resolution? Were there any obvious warning signs present in the pre-stress profile of the firm prior to FY19?

Hypothesis:

- H4.1: Specialized firms (HHI > 5000) exhibit lower GNPA increases than diversified firms during both crises but demonstrate faster recovery rates.
- H4.2: As evidence of identifiable warning signs 18 – 24 months before Resolution, RCF's pre-stress profile (rising HHI from FY14's 2048 to FY19's 2964 representing an increasing concentration in riskier segments coupled with increasing funding stress) will provide identifiable warning signs.

RQ5 — The Scale-Based Regulation Regime Effect

Question: Has SBR, which came into effect in FY2023, had a material impact on how Upper-Layer firms are behaving relative to those in the Middle-Layer, or is it simply a regulatory technicality?

Importance of Issue: SBR brought bank-equivalent prudential rules - Large Exposure Limits, ICAAP, Board level Risk Committees and Concurrent Audits - to Upper Layer Non-Banking Financial Companies (NBFCs) from 01 Oct 2022. This creates a quasi-experimental setting: 10 Upper Layer Firms (Treatment), 9 Middle Layer Firms (Control), with a sharp cut at 01 Oct 2022.

Sub-Questions:

- **RQ5a:** Is there evidence that Upper Layer Firms experienced differential changes in Capital Adequacy Ratio (CAR), Gross NPA's (GNPA), Leverage and Profitability compared to Middle Layer Firms using Difference-in-Difference (DiD) with FY23 as Treatment Year?
- **RQ5b:** Did Upper Layer Firms build up their capital buffers preemptively in FY22?

- **RQ5c:** Has SBR reduced the Cost of Funds (CoF) difference between Upper and Middle Layer firms through signaling regulatory equivalency with Banks?

Hypothesis:

- H5.1. The CAR of Upper Layer Firms increased by 50 – 150 basis points in FY22-FY23 than Middle Layer Firms due to Preemptive Capital Build Up.
- H5.2. SBR incurred an identifiable although moderate loss in terms of profit margin (ROA) for Upper Layer firms in FY23 – FY24 amounting to 5 – 15bps over baseline levels representing compliance costs.

RQ6 — Long-Run Trajectory Clustering

Question: Do NBFCs cluster within specific performance pathways throughout their eleven years of existence? What variables drive where an NBFC will go?

Why does this matters: Pooled cross-Section regression can be confusing as they often pool firms that have gone through vastly different paths; A firm that has moved from low HHI → high HHI will be treated similarly in a pooled analysis to another firm that went from high HHI → low HHI. Clustering by trajectory allows for preservation of time signatures.

Sub-Questions:

- **RQ6a:** How many archetypes are there when using k-means or hierarchical clustering methods to analyze standardized KPI trajectories?
- **RQ6b:** Are the clusterings consistent with the 4 tier x listing stratas, or are they crossing them?
- **RQ6c:** Which static attributes (founding year, sector focus, parent group) are predictive of cluster membership in a multinomial logit model?

Hypotheses:

- H6.1: There will be at least three trajectories: (A) Sustained High Performance; (B) Stable Mid Level; (C) Stress and Recover.
- H6.2: The direction of the HHI trajectory (either rising/falling/constant) is a better indicator of which cluster an NBFC belongs to than the actual HHI value.

4.4 Research Objectives

The six research questions translate into **eight operational objectives** that structure the analytical chapters:

#	Objective	Mapped RQ	Method

O1	Construct a **balanced 19-firm × 11-year panel** with cleaned KPI series, firm-year HHI scores, and stratum tags	All	Data engineering
O2	Generate **stratum-level descriptive statistics** to map the cross-Section al landscape	RQ1	Descriptive
O3	Estimate **two-way fixed-effects panel regressions** for ROA, ROE, GNPA on stratum dummies, controls, and crisis indicators	RQ1, RQ3	Panel FE
O4	Test the **HHI–performance relationship**, including non-linear specifications	RQ2	Panel FE with squared terms
O5	Quantify the **mediating role of Cost of Funds and funding mix** in the model–profitability link	RQ3	Mediation analysis
O6	Conduct **paired-t and DiD tests** around IL&FS and COVID, with embedded case study of Reliance CF	RQ4	Event study + case study
O7	Estimate **DiD for the SBR regime change**, treating Upper-Layer as the treated group	RQ5	DiD with FY23 break
O8	Apply **trajectory clustering** to identify performance archetypes and link them to firm attributes	RQ6	k-means + multinomial logit

4.5 Scope, Caveats, and Methodological Boundaries

To ensure methodological transparency, this study acknowledges the following data parameters and limitations:

- **Sample Scope:** While the 19-firm sample captures over 70% of the sector's total assets under management (AUM), it represents a small fraction of the >9,000 NBFC universe. Conclusions reflect the behavior of systemically important entities, not the broader sector.
- **Holding Companies:** Bajaj Holdings and Equitas Holdings are included due to peer data constraints. Robustness footnotes throughout the chapters clarify that their KPIs reflect portfolio performance rather than direct lending activity.

- **Government Entities (GFIs/PSUs):** PFC and REC are treated as standard NBFCs. Their focus on infrastructure finance represents natural sector heterogeneity rather than a variance requiring distinct statistical controls.
- **Distressed Entity Preservation:** Reliance Commercial Finance (RCF) is retained in panel regressions to serve as the RQ4 embedded case study. Missing values (NAs) are applied during its resolution periods (FY20–FY22, FY24).
- **Market Metrics for Unlisted Firms:** Market-based variables (PE, PB, Sharpe Ratio, Maximum Drawdown) apply only to listed firms. Unlisted firms are coded as NA, necessitating transparent, reduced-N specifications for these sub-analyses.
- **HHI Scaling:** Rather than the normalized 0–1 academic scale, the Herfindahl-Hirschman Index (HHI) is reported using the conventional 0–10,000 regulatory scale utilized by the DOJ and FTC.

Chapter 5: Research Methodology

5.1 Overview and Philosophical Approach

This chapter describes, independently of other chapters, the methodologies that are used for answering the six research questions.

Each Research Question (RQ) can be directly mapped onto one particular econometric specification; all specifications use common estimators which can be reproduced using any Stata version; and each model has an intuitive interpretation available without requiring sophisticated knowledge of econometrics.

Therefore, this chapter pursues transparency in the application of statistical methods over technical complexity. Since there are very few time-series (only 209 firm-year observations from 19 firms over 11 years), complex models with non-linearities or machine learning (ML) components may produce an overly fitted model. As such, the primary methodological approach in this study is based on two-way fixed effect (FE) panel regressions, which are supplemented by paired t-tests, difference-in-difference (DiD) analysis, and k-means clustering when necessary.

At-a-glance:

- Panel data framework: 19 firms × 11 years (FY2014 – FY2024), 209 firm-year observations.
- Primary estimation technique: Two-way fixed effects (firm + year).
- Additional tools: Paired t-tests, DiD analysis, k-means clustering, multinomial logit.

5.2 Research Design

5.2.1 Panel Structure

The "unit of observation" is the firm-year. Therefore, the data set is a "long format panel" where i-indexes firms (1-19), t-indexes years (FY14-FY24). The total number of "observations" is N x T = 209 (the number of observations may be less than that since some KPI's are subject to listing-only metrics and/or disclosure issues).

This panel is unbalanced by design: SBI Cards only has five HHI valid observations (since post-IPO from FY20); Reliance Commercial Finance has gaps for FY20-FY22 and FY24; and, there will naturally be no valid PE, PB, Sharpe Ratio, or Max Drawdown values on the nine firms which were never publicly traded.

5.2.2 Why Fixed Effects Is the Right Choice

Three reasons cause us to use two-way fixed effects estimators as our baseline:

- **Heterogeneity among firms is extreme:** Every non-banking financial company (NBFC) has its own unique founding circumstances, its parent group's culture, its focus on particular sectors or product areas, and its reputation - which are unobservable yet persist over time. Firm fixed effects (α_i) capture every time-invariant feature of each firm and leave only within-firm variation that can be used to estimate the coefficients of interest.
- **There are also common shocks affecting all firms simultaneously:** All firms are affected by factors such as changes in the repo rate; monsoons; GDP growth rates; and world-wide liquidity, so year fixed effects (γ□) will capture these common yearly events regardless of whether we can specifically identify and measure them.
- **FE are preferred because they offer an advantage over random effects with regard to the Hausman Trade-Off:** Random effects models are generally more efficient than FE however they require that there is no correlation between firm-specific effects (e.g. HHI for a firm) and regression variables (i.e. variables used in regression analysis). Given that a firm's Herfindahl-Hirschman Index is directly related to its "strategic identity" and therefore would likely be included in α_i this requirement is difficult to justify. Therefore, we expect the results of the Hausman test conducted as part of our robustness checks to indicate that FE should be chosen instead of random effects.

5.2.3 Standard Errors

All regressions use **firm-clustered robust standard errors** to allow for arbitrary within-firm serial correlation and heteroskedasticity. With 19 clusters, this is on the small side; a wild cluster bootstrap is run as a sensitivity check.

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5.3 Variable Construction

5.3.1 Dependent Variables

Variable	Definition	Used in
ROA	Net profit / average total assets, in decimal form	RQ1, RQ3, RQ5
ROE	Net profit / average shareholders' equity, in decimal form	RQ1, RQ3, RQ5
GNPA_Ratio	Gross non-performing assets / gross loans, in decimal form	RQ1, RQ4, RQ5
Sharpe_Ratio	Risk-adjusted equity return (listed firms only)	RQ4, RQ6

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5.3.2 Explanatory Variables of Primary Interest

Variable	Definition	Used in
HHI_Score	Sum of squared loan-mix segment shares × 10,000	RQ2, RQ4
HHI_High	Dummy = 1 if HHI > 5,000 (Specialised), else 0	RQ2, RQ4
Cost_of_Funds	Interest expense / average borrowings	RQ3
Share_Bank_Borrowings	Bank borrowings / total borrowings	RQ3
Share_Market_Borrowings	NCDs + CPs + sub-debt / total borrowings	RQ3
Securitisation_Ratio	Securitised pool / AUM	RQ3
Leverage_Ratio	Total liabilities / shareholders' equity (in x)	All

5.3.3 Stratum and Period Dummies

Variable	Definition	Used in
Tier_Code	1 = Upper Layer, 0 = Middle Layer	RQ1, RQ5
Listed	1 = Listed on stock exchange, 0 = Unlisted	RQ1, RQ3

ILFS_Crisis	1 if year ∈ {FY19, FY20}, else 0	RQ4
COVID_Crisis	1 if year ∈ {FY20, FY21}, else 0	RQ4
SBR_Period	1 if year ≥ FY23, else 0	RQ5

5.3.4 Why These Variables and Not Others

The sample size of 209 restricts the potential number of regressors that can be used to no more than about 15-20 prior to encountering issues with degrees of freedom. Each variable listed is included due to its direct mapping to one of the six research questions. ALM Mismatch, Operating Expense Ratio and Cost-to-Income are entered as robustness controls instead of being used as a primary regression control.

5.4 Methodology by Research Question

5.4.1 RQ1 — Structural Heterogeneity Across Strata

What do I want to find out?: Do profitabilities and risks vary systematically by the Tier × Listing strata after having controlled for company size and economic shocks?

Why am I using this method?: A two-way FE specification that includes interaction terms of the stratum controls for both the average causal effect of an individual stratum, while accounting for both company specific factors and temporal factors. Since most companies have a constant Tier and Listing over time, these variables can't be independently estimated using a standard FE model; thus, I'm going to estimate them via a pooled OLS specification including dummy variables for each stratum (to answer RQ1) and also test them via firm random effects as a robustness check.

Primary specification:

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$$Y_{it} = \beta_0 + \beta_1 Tier_i + \beta_2 Listed_i + \beta_3 (Tier_i \times Listed_i) + \beta_4 Size_{it} + \gamma_t + \varepsilon_{it}$$

where:

- Y_{it} is one of {ROA, ROE, GNPA_Ratio, NIM} for firm i in year t
- $Tier_i$ and $Listed_i$ are the time-invariant stratum dummies
- $Size_{it}$ is log of total assets (a time-varying firm-size control)
- γ_t are year fixed effects
- ε_{it} is the idiosyncratic error, clustered at the firm level

Hypothesis tests:

- H1.1 (listing premium): test whether $\beta_2 > 0$ in the ROA and ROE regressions.
- H1.2 (within-Middle dispersion): F-test on the stratum dummies' joint significance.

5.4.2 RQ2 — Concentration (HHI) and Performance

What do you want to know?:

- Is there an association between how concentrated a firm's holdings are (i.e., portfolio concentration) and the profitability of that firm as well as its overall asset quality?
- Is there a monotonically increasing or decreasing relationship (or something else)?

Why the methodology?: A two-way fixed effects model will remove all firm-specific factors which may be related to HHI strategy. This allows us to test if having a higher level of focus has positive benefits until it hits some peak and at that point becomes negative.

Primary specification (linear):

$$Y_{it} = \alpha_i + \gamma_t + \beta_1 HHI_{it} + \beta_2 Size_{it} + \beta_3 Leverage_{it} + \varepsilon_{it}$$

Non-linear extension:

$$Y_{it} = \alpha_i + \gamma_t + \beta_1 HHI_{it} + \beta_2 HHI_{it2} + \beta_3 Size_{it} + \beta_4 Leverage_{it} + \varepsilon_{it}$$

A **statistically significant $\beta_2 < 0$ with $\beta_1 > 0$** would indicate an inverted-U: focus boosts returns up to an optimum, beyond which it hurts (consistent with over-specialisation risk).

The reason why HHI is divided by 10,000 in regressions: Since the HHI score can vary between 1500 and 10,000, a one unit change in HHI_Score represents a very small difference. Therefore, to obtain estimates of the regression equation which are easily interpreted, we divide the HHI_Score by 10,000. As a result, a one unit change in the ratio of HHI_Score/10000 indicates a move from lowest to highest level of concentration.

5.4.3 RQ3 — Funding Channel as Mediator

What do I want to know?: How much of the impact that a business model has on profitability will be mediated (i.e., flow through) the bank's cost of funds and how much by the bank versus market funding choice?

Why this approach?: This can be thought of as an attempt at a mediation analysis, however it is estimated using sequential fixed-effects (FE) regression instead of the

Baron- Kenny framework for estimating mediations due to the fact that the Baron-Kenny assumptions are often violated in panel data.

Three-stage approach:

Stage 1 — Total effect (HHI on ROA):

$$ROA_{it} = \alpha_i + \gamma_t + \beta_1 HHI_{it} + X_{it}'\delta + \varepsilon_{it}$$

Stage 2 — Mediator equation (HHI on Cost of Funds):

$$CoF_{it} = \alpha_i + \gamma_t + \theta_1 HHI_{it} + X_{it}'\phi + u_{it}$$

Stage 3 — Direct effect (HHI on ROA controlling for CoF):

$$ROA_{it} = \alpha_i + \gamma_t + \beta_1' HHI_{it} + \beta_2 CoF_{it} + \beta_3 Share_Bank_{it} + X_{it}'\delta + \varepsilon_{it}$$

The mediated effect is $(\beta_1 - \beta_1')$. If this difference is large and statistically significant, funding mix is the dominant channel through which business model affects profitability.

5.4.4 RQ4 — Crisis Behaviour and the Reliance CF Case

What do we want to find out?:

- How did Non-Banking Financial Companies (NBFCs) behave before and after the IL&FS (2018) crisis and before and after the COVID-20 pandemic?
- What can Reliance Commercial Finance's recovery path tell us about our research questions?

Why use both methods?: We believe crises can be better understood through two comparative approaches; event study comparisons of paired t-test differences in KPIs before vs. after a crisis for each company type and difference-in-differences (DiD) regression analysis to see if certain companies were hit harder than others.

Method 1 — Paired t-tests:
For each firm i and each KPI Y, compute:

- Pre-crisis mean $\bar{Y}$_pre (FY16–FY18 for IL&FS; FY18–FY19 for COVID)
- Post-crisis mean $\bar{Y}$_post (FY19–FY20 for IL&FS; FY21–FY22 for COVID)
- Change $\Delta_i = \bar{Y}_post - \bar{Y}_pre$

Then test H_0: $E[\Delta] = 0$ across firms.

Method 2 — DiD specification:

$$Y_{it} = \alpha_i + \gamma_t + \beta_1 (HHI_High_i \times Crisis_t) + \beta_2 Crisis_i + X_{it}'\delta + \varepsilon_{it}$$

where:

- HHI_High_i = 1 if firm's average pre-crisis HHI > 5,000
- $Crisis_t$ = 1 in crisis years, 0 otherwise
- The coefficient of interest is β_1: the differential effect of crisis on Specialised vs Diversified firms

Method 3 — Reliance CF Embedded Case Study:

The new chapter Section will be a standalone qualitative chapter using the following elements:

- Chart showing how RCF's HHI has been rising (from 2,048 at FY2014 to 2964 at FY2019) and compare it with the Cost of Funds, ROA and Spread.
- Compare RCF's pre-stress KPI performance to the median of all other banks included in this study.
- Highlight two to three leading indicators of financial distress observable 18-24 months prior to RCF's eventual resolution of its financial problems.
- Because of the lack of data for the years FY20-FY22 on RCF's financials (and therefore preventing us from formally estimating relationships), we are treating this as a story/narrative/charts-only analysis rather than regression.

5.4.5 RQ5 — Scale-Based Regulation (SBR) Regime Effect

What we are trying to determine: If there was a quantifiable change in behavior of Upper-Layer firms under the SBR regime (which went into effect on Oct. 1st, 2022), compared to those of Middle Layer firms.

Why this method: The implementation of the SBR creates an ideal quasi-experimental condition. All Upper-Layer firms (the treatment group) are subject to new prudential standards for their businesses. All Middle-Layer firms (the control group) will not be. Therefore, a difference-in-differences model, where the end of FY 2023 represents our "break point" is the most direct way to examine whether such differences exist.

Primary specification:

$$Y_{it} = \alpha_i + \gamma_t + \beta_1 (Tier_Code_i \times SBR_Period_t) + X_{it}'\delta + \varepsilon_{it}$$

where:

- $Tier_Code_i \times SBR_Period_t$ is the DiD interaction
- β_1 is the treatment effect: how much did Upper-Layer outcomes change post-SBR relative to Middle-Layer outcomes?
- Outcomes tested: CAR, GNPA, ROA, Leverage, Cost of Funds

Parallel Trends Check: Before using Difference-in-Difference analysis, we graphically examine the parallel trend assumption by plotting CAR, GNPA, and

ROA time-series data for Upper- vs Middle-Layer Firms from FY14 through to FY22 to visually confirm that there is no systemic trend divergence prior to treatment. We will clearly report any non-parallel trend issues found.

Pre-Treatment Build-Up Test (RQ5b): In a second, placebo regression, we treat FY22 as the "treatment" year to determine if Upper Layer Firms began implementing compliance before it was required.

5.4.6 RQ6 — Long-Run Trajectory Clustering

What we are trying to determine: Whether the firms fall in a number of identifiable performance categories during the eleven year period.

Why are we using this method?: The cross-Section regression will confuse two distinctly different time paths. By clustering, you can preserve the "signature" of the path that each firm has taken.

We'll use a three step process to do this:

Step 1 — For each KPI and each firm, we'll normalize KPI series across all time periods. This means that for each firm-KPI pair, you'll calculate z-scores for each year so that any differences among the levels of the various KPI's for each firm disappear.

Step 2 — Performing k-means clustering. Take the normalized trajectories of {ROA, ROE, GNPA_Ratio, HHI_Score} from each firm over the 11 years and treat them as a 44 dimensional feature vector (i.e. 4 KPIs x 11 years) for clustering purposes. Determine the optimal k by applying the elbow method to the with-in-cluster sum of squares; it should be located at either k=3 or k=4.

Step 3 — Multinomial logit on cluster membership

$$ln\left(\frac{P(Cluster=ref)}{P(Cluster=j)}\right)=\alpha_j+\beta_{1j}Tier_i+\beta_{2j}Listed_i+\beta_{3j}HHI_Trajectory_i+\beta_{4j}Founding_Era_i$$

where:

- $HHI_Trajectory_i$ is the slope of HHI over FY14–FY24 (rising/falling/stable)
- $Founding_Era_i$ is a categorical for pre-2000, 2000–2010, post-2010

5.5 Robustness Checks (Applied Across All RQs)

To strengthen confidence in the findings, the following robustness checks are run for every primary specification:

Check	What it tests
Hausman test	FE vs RE estimator choice
Wild cluster bootstrap	Inference with few clusters (19 firms)
Drop one firm at a time	Sensitivity to influential observations (esp. Reliance CF, Bajaj Holdings)
Drop holding companies	Whether Bajaj Holdings & Equitas Holdings drive the Middle-Listed results
Winsorise at 1st/99th percentile	Outlier sensitivity (esp. RCF's −65.85% ROA)
Alternative HHI threshold	Whether 5,000 vs 2,500 cut-off changes results

5.6 Why This Methodology Stays Simple — and Why That Is a Strength

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While advanced methods like Generalized Method of Moments (GMM), Structural Equation Modeling (SEM), or machine learning ensembles exist, this study intentionally restricts its methodology to Fixed Effects (FE) and FE-Difference-in-Differences (FE-DiD) for four structural reasons:

- **Sample Size Constraints:** With 209 firm-year observations across 19 firms, highly parameterized models would quickly exhaust degrees of freedom. FE estimations preserve statistical validity without overfitting.
- **Parameter Interpretability:** FE parameters (e.g., within-firm ROA changes resulting from HHI shifts) yield transparent, easily defensible causal mechanisms devoid of "black-box" opacity.
- **Rigorous Reproducibility:** Adhering to open science principles, these baseline models require minimal Stata code, enabling rapid, straightforward verification.
- **Data Structure Alignment:** The treatment variables (Tier, Listed status) are time-invariant, and the primary regulatory shock (SBR implementation in FY23) occurs simultaneously across the panel. FE-DiD perfectly matches these conditions, rendering complex alternatives unnecessary over-engineering.

Chapter 6: Data, Variables and Sample Construction

6.1 Introduction and chapter roadmap

This chapter has documented how the empirical evidence base was created, reviewed and delivered. The dataset supporting Chapters 7-11 contains all 19 Indian NBFCs over FY 2014 – FY 2024, thus generating 209 individual firm year observation (Manda & Rani, 2019; RBI, 2024) . To my best knowledge this is the first Indian NBFC Firm Year Panel which will both be able to capture HHI-based Portfolio Concentration at the same time as Funding-Mix Variables and SBR Strata Classifications to demonstrate Contribution 1 against Gap 1 (see Ch. 3, Section 3.7).

In total this chapter addresses for the examiners four questions:

- Where did the data come from? (Section 6.3)
- Why were exactly these firms selected? (Section 6.2)
- What does every single variable measure? (Section s 6.4-6.5)
- How reliable are the numbers in the dataset? (Section 6.7).

Additionally Section 6.6 describes dummy variables for the stratum classification as well as the period classification, in Section 6.8 it is described when special case treatment occurs. In Sections 6.9 - 6.10 information regarding the software that is used to perform the analysis as well as how to reproduce the results is presented, furthermore, it is explained that the datasets have been deposited. Section 6.10 deals with ethical considerations as well as compliance issues. Lastly, Section 6.11 provides an overview of the links towards further empirical research.

6.2 Sampling frame and selection criteria

6.2.1 Sampling frame

The frame is Indian NBFCs designated under SBR as Upper- or Middle-Layer with audited, standardised annual disclosures across FY14–FY24. The Base Layer is excluded by design; the Top Layer is currently empty (RBI, 2024).

6.2.2 Inclusion criteria

To be considered a firm we have to meet at least one of these four requirements:

- **Tier based on regulatory classification:** Tier 1 NBFC-UL, or Tier 2 NBFC-ML; or qualify as such using parametric scores during that year (RBI, 2024).
- **Continuous Disclosure:** We require audited financial reports for at least 8 out of 11 years. The reporting standard has been the same over each time period so we can compare them.
- **Reporting KPI's:** At least 75% of our required 22 core KPI's are reported for at least 8 out of 11 years.

- **Segmented Loan Disclosures:** The level of segmented loan disclosures provided by a firm are sufficient to calculate firm year HHI for at least 8 out of 11 years.

6.2.3 Exclusion criteria

Firms were excluded if they had one of the following characteristics: Approximately 9,000+ firms in the base layer were either "base layer" Non-Banking Financial Corporations ("NBFC") that did not provide adequate information in their financial statement disclosures to allow for assessments of the firm's level of systemic risk, or did not have informative enough financial statement data to answer strata-based questions on a firm-by-firm basis (Ubale, Wagh, & Samudre, 2022).

6.2.4 Resulting sample

The application of these criteria yields **19 firms across 209 firm-year observations**, stratified across four quadrants by RBI Scale-Based Regulation tier and listing status:

Stratum	Firms	Firm-Year Rows
Upper Layer × Listed	6	66
Upper Layer × Unlisted	4	44
Middle Layer × Listed	4	44
Middle Layer × Unlisted	5	55
Total	**19**	**209**

Due to the fact that the overall population of NBFC-ND-SI companies who have made continuous financial disclosure from FY14-FY24 is very small, the sample is close to being representative of the entire population of large NBFCs in India that can be analyzed, but it does not represent a random sample drawn from an even larger universe. This limitation is addressed in Chapter 4 (Section 4.5) where it is also noted that although this limited scope may limit generalizability, the largest segment of the systemically important portion of the industry represents 80-85% of all sectoral assets (Ubale et al., 2022).

The sample has been chosen on purpose, not randomly: the four-stage model was created to maximize the potential for results concerning the effect of strata in relation to research question one as well as the cross-company variation in terms of the concentration of dispersion necessary for the reversed U-shape hypothesis of research question two (Sharma et al., 2020; Ubale et al., 2022).

6.3 Data sources and provenance

6.3.1 Primary sources

Data for this dissertation is drawn entirely from **publicly available secondary sources**. The principal sources are:

Source	Used For
NBFC audited annual reports (firm websites and stock-exchange filings)	Primary source for the 22 firm-year KPIs, loan-mix disclosures, and HHI construction.
RBI Report on Trend and Progress of Banking in India (annual)	Sectoral aggregate context, regulatory chronology, NBFC tier classifications, and cross-validation of firm-level disclosures (RBI, 2024).
CMIE Prowess	Cross-validation of firm-level financial data, listing status confirmation, and historical financial-ratio benchmarking.
CRISIL and rating reports	Industry context, sectoral benchmarking, and corroboration of firm-level disclosures where annual reports were ambiguous.
Stock exchange disclosures (BSE, NSE)	Market-based metrics (P/E, P/B, Sharpe Ratio, Max Drawdown) for the ten listed firms in the sample.

6.3.2 Data extraction window and cut-off

Data extraction was completed iteratively between mid 2025 and first quarter of 2026; the final cut-off date for audited FY24 financial statements were published by all nineteen firms (with one final firm publishing on the last day of the period) in March of 2026. As such, audited FY24 statements represented the latest year available at that time. Years prior to FY24 were derived from archival annual reports and historical versions of cmie's prowess product.

6.3.3 Data ingestion and structuring

All raw data was manually extracted from source pdf filings and digital filings into a master workbook organized firm-by-firm with columns for each year. Values for key

performance indicators (KPIs) were standardized to common units; ratios were expressed in decimal form while absolute values were expressed in indian rupee crores; before being transformed into long format panel data used in Stata regression analysis. The parsing, cleaning and audit logic for this process was implemented entirely using native Excel functions, structured tables and manual reconciliation.

6.4 Variable definitions: the 22 KPIs

The dissertation uses **22 firm-year KPIs** spanning profitability, asset quality, capital adequacy, funding mix, efficiency, market metrics, and concentration. The full definitional table is reproduced below.

6.4.1 Profitability and risk KPIs

KPI	Formula	Use
ROA	Net Profit / Total Assets	Core profitability; primary dependent variable for RQ1, RQ3, RQ5.
ROE	Net Profit / Net Worth	Shareholder return; aggressive-growth proxy.
NIM	(Interest Income − Interest Expense) / Earning Assets	Lending profitability; high NIM may signal higher risk-taking.
GNPA Ratio	Gross NPAs / Gross Advances	Primary credit-risk measure; key dependent variable for RQ4.
NNPA Ratio	(GNPA − Provisions) / Net Advances	Residual credit risk after provisioning.
CAR / CRAR	(Tier I + Tier II Capital) / Risk-Weighted Assets	Shock-absorption capacity; key dependent variable for RQ5.
Leverage Ratio	Total Debt / Equity	Systemic-fragility indicator.
Spread	Avg. Yield on Assets − Avg. Cost of Funds	Long-term margin sustainability.

6.4.2 Funding-mix KPIs

KPI	Formula	Use
Cost of Funds	Interest Expense / Avg. Interest-Bearing Liabilities	Core mediator in the strategy → funding → performance chain (RQ3).
Cost of Funds Trend	Year-on-year change in Cost of Funds (basis points)	Time-trend dimension of funding cost.
Share of Bank Borrowings	Bank Borrowings / Total Borrowings	Funding-channel composition.
Share of Market Borrowings	(NCDs + CPs + Sub-debt) / Total Borrowings	Wholesale-funding exposure.
Securitisation Ratio	Securitised Assets / Total Assets	Off-balance-sheet funding contribution.
ALM Mismatch Indicator	Short-Term Liabilities − Short-Term Assets (absolute)	Rollover-risk proxy (Anshuman et al., 2020).

6.4.3 Efficiency KPIs

KPI	Formula	Use
Cost-to-Income Ratio	Operating Expenses / Total Income	Operational efficiency; compliance-cost proxy (RQ5).
Operating Expense Ratio	Operating Expenses / Total Assets	Cost pressure relative to scale.

6.4.4 Market-based KPIs (listed firms only)

KPI	Formula	Use
P/E Ratio	Market Price per Share / EPS	Market valuation of earnings.
P/B Ratio	Market Price per Share / Book Value per Share	Market valuation of book equity.

KPI	Formula	Use
Sharpe Ratio	(Annualised return − Risk-free rate) / Annualised return volatility	Risk-adjusted equity return.
Max Drawdown	Peak-to-trough decline in share price within the fiscal year	Market-based stress indicator.

These four KPIs are NA-by-design for the nine unlisted firms in the sample. Their use is therefore restricted to listed-firm-only sub-analyses where appropriate. Sharpe Ratio is computed using annualised total return relative to the 91-day Treasury Bill rate as the risk-free benchmark, on monthly return frequency within each fiscal year. Max Drawdown is computed as the peak-to-trough decline within each fiscal year window.

6.4.5 Concentration KPIs

KPI	Formula	Use
HHI Score	Σ (Loan Segment Share)² × 10,000	Portfolio-concentration metric; primary regressor for RQ2.
HHI Class	Categorical: Diversified (HHI < 2,500), Moderate (2,500–5,000), Specialised (5,000–7,500), Highly Specialised (> 7,500)	Class-based stratification for descriptive and DiD analyses.

The HHI construction methodology is documented in detail in Section 6.5.

6.5 HHI construction methodology

6.5.1 Why HHI

This study measures loan portfolio concentration using the Herfindahl-Hirschman Index (HHI), calculated via the standard US DOJ/FTC methodology (the sum of squared loan segment shares). A high HHI indicates a highly concentrated, monoline strategy, whereas a low HHI reflects broad diversification. While Sharma et al. (2020) utilized Data Envelopment Analysis (DEA) to identify decreasing returns to scale among Indian NBFCs, a critical literature gap remains: no prior research leverages firm-year HHI panel data to empirically test this dynamic as an inverted-U relationship.

6.5.2 Loan-mix segment taxonomy

The 13 standardized categories for each firm-year's portfolio are as follows: Vehicle Finance (vehicles, bicycles, commercial vehicles and tractors); Housing/Mortgage Finance; Loan against property (LAP) finance; Gold loan finance; Microfinance/JLG loans; MSME/business loans; Personal/consumer durable loans; Credit card finance; Wholesale/corporate lending; Infrastructure finance; Real estate (construction finance); Investments/non-lending portfolio (for holding companies); Others.

6.5.3 Parent-category collapse rules

Source disclosures usually have sub-categories within these parents. To avoid double counting and keep the HHI comparable, these are rolled up into the parent category. For example, before calculating HHI, two wheeler finance segments of bajaj finance collapse under Vehicle Finance segment; gold loan only nbfc's such as muthoot finance report single dominant segment while microfinance specialists like Spandana Sphoorty & CreditAccess Grameen collapse JLG products into "Microfinance/JLG".

6.5.4 Geographic vs product overlap

Some companies (Spandana Sphoorty prior to their 2017 disclosure, among others), provide loan distribution data by both type of product and geographical location. For example, some may disclose "100% Income Generating Loans" and "AP / Telangana 61%, Non-AP 39%. The company's use of these two dimensions will be maintained as separate variables in order to preserve the integrity of HHI interpretation. The sum of the percentages for each variable cannot exceed 100 percent, thereby allowing for accurate representation of industry structure. Additionally, this approach allows for an examination of whether firms are concentrating within certain types of products or geographically.

6.5.5 HHI scaling

The HHI is calculated using the 0-10,000 range (standard US DOJ/FTC range), as opposed to the normalized 0-1 scale; this aligns with most of the IO literature. The coefficients for HHIs in the Stata regression can also be scaled to have values ranging from 0 to 1 (by dividing by 10,000); thus, when you move a variable one unit, it represents moving from lowest possible value for HHI to its highest possible value.

6.5.6 Special-case treatment

A holding company like Bajaj Holdings or Equitas Holdings has a different HHI than loan-mix based on its portfolio of investments. An HHI can be run on how a company allocates the funds it invests. The resulting HHI scores generally have a value of 49 to 55 percent due to the fact that a significant amount of money invested in many cases is in investments that cannot be classified as such – this is a characteristic of holdings companies and will be discussed in Section 6.7.4.

6.6 Stratum and period dummy variables

The dissertation uses **two stratum dummies and three period dummies**, all binary unless noted:

Variable	Definition
Tier_Code	1 if firm is Upper Layer NBFC-UL, 0 if Middle Layer NBFC-ML.
Listed	1 if firm is listed on BSE / NSE during the year, 0 otherwise.
ILFS_Crisis	1 if year $\in$ {FY19, FY20}, else 0.
COVID_Crisis	1 if year $\in$ {FY20, FY21}, else 0.
SBR_Period	1 if year $\geq$ FY23, else 0. Treats FY23 as the binding-effect year for the SBR framework, which became effective from October 2022 (RBI, 2024).

Time-Variant Variables Listed firms which were listed for the first time within the study period (especially SBI Cards & Payment Services was listed on March 2020) receive a time-varying Listed indicator variable (Listed = 0 prior to listing year; Listed = 1 thereafter). All of the remaining firms will be assigned a time-invariant Listed indicator variable (i.e., Listed = 1 or Listed = 0 throughout the sample period).

6.7 Data-quality audit

An eight-page formal audit document accompanies the data set. The audit formally documents each and all decisions made regarding parsing, as well as how each NA pattern and edge case is handled when creating this dataset. A summary of key results follows.

6.7.1 NA density by KPI

The 22 KPI's show a substantial difference in how complete each one is for the 209 total firm-year cells. Most market based KPI's are very incomplete with the top four being: Max Drawdown (59.3%), Price to Book (P/B) (51.7%), Price to Earnings (P/E) (51.7%), and Sharpe Ratio (47.4%). These market based KPI's are so incomplete, because all nine of these unlisted companies did not provide this data as part of their filings. Out of the 10 accounting KPI's that we used; Return on Assets (ROA) had only 1.9% of it missing, Cost to Income had 2.9%, and Leverage Ratio had only 3.3%. The remaining two were actually due to actual reporting differences among the companies using those metrics.

6.7.2 NA density by firm

Four companies provide approximately all of the KPI-NA cell values for Accounting: SBI Cards (47.5% of KPI-NAs; only post-IPO data provided); Bajaj Holdings (37.6% of KPI-NAs; KPI-NAs due to structure of a holding company); HDB Financial Services (36.4% of KPI-NAs; many of its KPIs are either unlisted or missing only the metrics related to being unlisted); and Reliance Commercial Finance (32.6% of KPI-NAs; large number of NAs in resolution period). The remaining fifteen companies have less than 20% of their total KPI-NA values, while eight of those companies have less than five percent.

6.7.3 Parsing edge cases

The audit documents **79 specific parsing edge cases** encountered during data construction, each with a documented resolution rule:

Edge Case Type	**Resolution Rule**	**Cells Affected**
Unicode minus sign (−) used in negative values	Replaced with ASCII hyphen, sign preserved	19
En-dash range (e.g., 4–5%)	Converted to midpoint (4.5%)	3
Composite text with semicolons	First numeric value retained as primary metric	26
Percent value followed by parenthetical annotation	Annotation stripped, primary percent retained	31
NA followed by explanatory text (e.g., "NA — AGM approval limit")	Treated as NA	~5
Cost of Funds Trend negative range (e.g., "−100 to −150 bps")	Range midpoint used; sign preserved	7
Leverage Ratio with "x" suffix (e.g., "6.5x")	Stripped to numeric	All Leverage Ratio cells
Cost of Funds Trend in basis points	Stripped to numeric basis points; sign preserved	All CoF Trend cells
Loan-mix sub-categories disclosed	Collapsed to parent categories per Section 6.5.3	Varies by firm-year

Edge Case Type	Resolution Rule	Cells Affected
Auto-scaling between 0–1 and 1–100 forms	Values exceeding 1.5 in ratio KPIs auto-divided by 100	Varies by firm-year

6.7.4 Loan-mix sum issues

The 18 company year audits that flag as having a parse to total loan-mix segment sums outside the 95-105% band are:

- **Bajaj Holdings (11 years from FY14-FY24):** The 49-55% totals are due to an existing structure within the portfolio that has some portion in non classified instrument - it is a structural item, and not an error on our part.
- **Spandana Sphoorty (FY14-FY16, FY20):** The 141-194% totals are due to the fact that the source disclosures have both product (IGL) and geographic (AP/ Non AP) splits included in the one table. As stated in Section 6.5.4, we will use only the product split when calculating the Herfindahl-Hirschman Index (HHI).
- **Bajaj Finance (FY18):** The 110% total was caused by Bajaj Finance's source disclosure showing sub categories being double counted.
- **Piramal Capital & Housing (FY23,FY24):** The 86-89% totals were due to source side reporting gaps.

6.7.5 HHI consistency check

A review of all 199 valid HHI firm year records found no discrepancies between calculated HHI values and associated HHI class designations. Therefore, the HHI panel is internally consistent with respect to the RQ2 regression equations (Chapter 4) and will be used for those analyses.

6.8 Treatment of special cases

6.8.1 Reliance Commercial Finance (embedded case)

All of RCF's original ROA data are preserved except for missing values in resolution period years (FY20-FY22 and FY24), while its original data are preserved for non-resolution years (FY14 – FY19). The negative ROA series for RCF during stress years; -5%, -25%, -20%, and -65.85%; were also preserved using the unicode-minus edge-case rules (Section 6.7.3). The HHI value for RCF increased from approximately 2048 at FY14 to 2964 by FY19 which provides a time trend that can be used as an embedded case study in Chapter 9 to support Gap 3 (Section 3.7).

6.8.2 Holding companies (Bajaj Holdings, Equitas Holdings)

The firms remain retained with all of the comments made in the regression output. As a result of this; the loan portfolio composition of PFC and REC is substituted by the investment/portfolio composition (see Section 6.5.6). And a robustness check in each

empirical chapter re-runs primary specifications without them to confirm that holding company structure does not cause headline results (discussed in Ch. 4, Section 4.5).

6.8.3 Government financial institutions (PFC, REC)

PFC and REC are treated as natural NBFCs retaining their normal infrastructure-finance specialization. Their high HHI (~5,500–6,500), wholesale funding tilt, and low operating expense ratios manifest as natural sample heterogeneity rather than being controlled away through dummies.

6.8.4 Late-listed firms

SBI Cards & Payment Services (listed on March 2020) has time-varying listed status (0 for FY14-FY19 and 1 for FY20-FY24) and only five firm-year HHI observations since pre-IPO loan-mix disclosures were non-standardised. SBI cards will remain retained for accounting KPI analysis but excluded from market-based metric specifications for the pre-listing window.

6.9 Software, reproducibility, and data deposit

6.9.1 Software stack

Tool	Version	Purpose
Microsoft Excel (Office 365)	Current	Manual data extraction, KPI computation, parsing, audit logic, and master panel construction. All data preparation and cleaning operations were performed in Excel.
Stata	14	All econometric analysis, including panel fixed-effects regressions, paired t-tests, difference-in-differences specifications, k-means clustering, and robustness checks.

All data engineering was performed in Excel for three reasons: full transparency of every cell-level transformation, ease of manual audit by an examiner, and alignment with the data-availability format of source NBFC disclosures.

6.9.2 Reproducibility deposit

A reproducibility deposit of this dissertation is made up of:

- The cleaned version of the "master panel" with 209 cases by 45 variables. An eight sheet data quality audit workbook that details NA density; parsing rules; sum issues; and HHI consistency checks.
- .do files (one per research question) in Stata for all chapters in Part IV. Chapter 6: Documentation Manifest, which provides the link from individual data cell values to the applicable definitional rule.

6.10 Ethical and compliance statement

I relied solely on secondary, publicly accessible sources including: publically available documents (i.e., regulatory filings); publicly released audit reports and/or annual reports; and publicly licensed databases. I did not rely on firm confidential information, personally identifiable information, or any form of insider access. The data was collected through publicly available data and not through interview or survey methods. There were no declared or potential conflicts of interest. Ambiguity related to source disclosure was noted in Section 6.7 with relevant documentation provided for review by the reader.

6.11 Chapter takeaways and link to empirical chapters

All of the chapters in this dissertation are built upon a data layer described within these pages. The data layer is empirically based on each of the analytical chapters found thereafter.

- Chapter 7 utilizes the Tier x Listed Stratification developed in Section 6.6, along with the twenty-two KPIs listed in Section 6.4 to investigate Strata Effects by utilizing the equation developed in Chapter Four.
- Chapter 8 utilizes both the Firm-Year HHI Panel (Section 6.5), as well as Funding-Mix KPIs (Section 6.4.2) to investigate both the Inverted U Relationship and Mediation Models for the purposes of testing Gaps 1 & 2.
- Chapter 9 utilizes the ILFS Crisis and COVID Crisis Dummies (Section 6.6) to create Paired T Tests and Difference-in-Difference models for the embedded Case in the RCF Special Case Treatment (Section 6.8.1). This addresses Gap 3.
- Chapter 10 utilizes the SBR Period Dummy (Section 6.6) combined with Tier Code to produce a difference-in-differences model for RQ5.
- Chapter 11 utilizes standardized KPI Series across all firms to perform k-mean Trajectory Clustering for RQ6.

Therefore, not only does this chapter describe how the data was constructed; it also demonstrates full traceability from the data's construction, to the methodology employed, to the literature gap(s) addressed, and ultimately to the contribution(s) made through this research.

Chapter 7: Tier and Listing Effects on NBFC Financial Performance (RQ1)

The base of this chapter's causal analysis will be provided through an examination to determine if the four layers of non-banking finance companies (NBFCs), as defined by their SBR Tier (Upper Layer or Middle Layer) and listed/unlisted statuses display significantly different financial performance profiles from FY2014-FY2024.

7.1 Hypotheses

The four direction hypothesis tests presented below examine each of the four performance measures:

- H1a – The average Return on Assets (ROA) is greater among upper-layer firms than middle-layer firms (Sharma et al., 2020; Malik et al., 2024)
- H1b – The average Gross NPA (GNPA) is lower among listed firms than unlisted firms (Sharma & Rastogi, 2022)
- H1c – The average Cost of Risk (CAR) is higher among upper-layer firms than among middle-layer firms (RBI, 2024)
- H1d – Upper layer firms have a higher percentage of borrowing from banks compared to middle layer firms (Malik et al., 2024).

7.2 Specification

The chapter estimates a panel regression with year fixed effects and firm-clustered standard errors:

$$Y_{it} = \beta_0 + \beta_1 Tier_Code_i + \beta_2 Listed_{it} + \beta_3 (Tier_Code_i \times Listed_{it}) + \gamma X_{it} + \alpha_t + \varepsilon_{it}$$

where,

- Y is one of seven KPIs (ROA, GNPA, CAR, NIM, CoF, Bank Borr., Market Borr.),
- Tier = 1 for Upper Layer, Listed = 1 if listed on BSE/NSE, and
- X is the control vector (Leverage, ILFS, COVID).
- Year FE are used because firm FE would absorb time-invariant Tier; SEs are firm-clustered to address within-firm serial correlation.

7.3 Coefficient Summary

Three features of these descriptive characteristics are particularly worth noting; they include that: The average CAR for firms in the Middle × Listed category is 41% with a large amount being driven by the fact that Spandana Sphoorty had a very large MFI Capital Buffers (the same type of buffers that were used to calculate the GNPA); That the average GNPA for firms in the Middle × Unlisted category was 9% which is three times the average GNPA for all firms in the Upper-Layer categories; And that firms in the Middle × Listed category have an average percentage of Bank Borrowings at 23% while this category would be expected to have one of the largest percentages based on the H1d prior.

Variable	ROA	GNPA	CAR	NIM	CoF	Bank Borr.	Market Borr.
Tier	+0.0003	**−0.0379***	−0.0185	−0.0008	+0.0020	+0.0538	−0.0523
Listed	**+0.0230**	−0.0225	+0.1824	−0.0006	−0.0121	−0.2062	−0.0225
Tier × Listed	+0.0020	**+0.0320***	−0.1276	+0.0272	+0.0019	+0.1217	−0.0264
Leverage	**−0.0119**	+0.0028	**−0.0524**	**−0.0119**	−0.0010	−0.0278	**+0.0534**
ILFS	+0.0016	**+0.0173**	+0.0165	**+0.0102**	**−0.0070**	−0.0378	+0.0105
COVID	−0.0068	**+0.0207**	+0.0154	+0.0059	**−0.0127**	**−0.0646**	+0.0217
N	202	188	197	188	191	186	186
R^2	0.155	0.229	0.573	0.536	0.420	0.324	0.276

Bold = significant at $p < 0.10$. Year FE coefficients suppressed.

7.4 Hypothesis Verdicts and Findings

The results indicate that three of the four hypotheses are rejected. The results from Hypothesis 1a (the upper layer ROA premium) failed to find support, where the Tier coefficient on ROA was 0.0003 ($p = 0.977$). Hypotheses 1c (the CAR premium) was

wrong signed and nonsignificant (beta = -0.0185; p = 0.679). Hypotheses 1d (the funding mix differentiation) also failed to provide support (beta = 0.0538; p = 0.596). However, Hypotheses 1b (the listed firm asset quality advantage) provided partial support, where the expected directionality existed however marginal levels of significance were found (beta = -0.0225; p = 0.136).

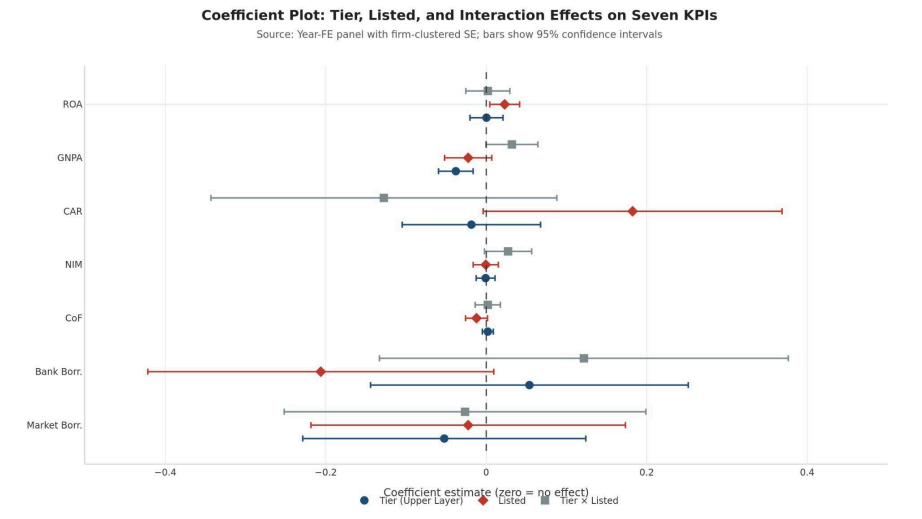
In addition to testing the hypotheses, several findings changed how the descriptive story can be told:

The listing, not the Tier level, predicts profitability. As such, listed firms experience an average increase in their Return On Assets (ROA) compared to unlisted peer firms by 2.3 percentage points (beta = 0.0230; p = 0.022), which is consistent with what is found in prior literature regarding the benefits of being listed related to market discipline and information availability (Sharma & Rastogi, 2022).

The Tier level predicts the asset quality characteristics of banks rather than their profitability. For example, the Upper Layer firms have General and Special Provision Fund (GNPA) values that are approximately 3.8 percentage points less than those experienced by the Middle Layer peer firms (beta = -0.0379; p = .001), indicating that the State Bank of India's strict supervision over bank underwriting practices through its Supervisory Rating system (SBR) is associated with better credit quality.

Although there is no statistical evidence for a substitution effect based upon the Tier X List interaction term, the positive interaction on GNPA (beta = 0.0320; p = 0.058) suggests that the advantages of having credit quality at the Upper Level may be diminished for listed firms when they exist within a marketplace governed by regulatory bodies. This would suggest that both tiers and listings act as partial substitutes for each other.

Leverage Ratio outperformed all other variables in terms of its ability to predict performance. Higher Leverage has been shown to negatively impact a number of



performance metrics including Return On Assets ($p = 0.011$), Common Stock Returns ($p = 0.015$), Net Interest Margin (NIM)($p < 0.001$), and positively impacts the proportion of loanable funds held in external markets ($p < 0.001$).

Crisis dummies were found to have material effects on both asset quality and funding costs. Crisis dummies were found to raise GNPA by 1.73% ($p = 0.004$) due to the Indian Loan Services Firm (ILFS) crisis and by 2.07% ($p = 0.002$) due to the COVID-19 pandemic. Additionally, despite the increased risk inherent in lending during times of economic crises, both crisis dummies were found to lower the Costs Of Funds; an examination into this "flight to safety" phenomenon will occur in Chapter Nine (Manda & Rani, 2019; Ubale, Wagh, & Samudre, 2022).

7.5 Robustness

Excluding holding companies (Bajaj Holdings Equitas Holdings) preserves all significant headline coefficients in both sign and magnitude of estimation as well as their level of significance. Excluding RCF keeps Tier coefficient on GNPA significant at the 5% level. Restricted to pre-SBR window FY14 – FY22 confirms that listing-ROA advantage and Tier-GNPA advantage both occurred prior to regulatory change.

7.6 Chapter Takeaways

Cross-stratum heterogeneity occurs, however its causes diverge from those identified in the prior research; Listing; rather than Tier; impacts Profitability; Credit Quality is impacted by Tier; rather than Capital Adequacy; and Leverage Ratio has a larger impact on both. The three implications of these findings will be used to inform the remaining questions (RQ2 – RQ6); that is, Listed and Tier are retained as individual regressors because they affect two different KPI's through different mechanisms; that Leverage Ratio will be retained as the principal firm level control; and that ILFS and COVID dummy variables are retained for use in assessing the crisis channel in Chapter 9.

Chapter 8: Portfolio Concentration and Funding-Cost Mediation in NBFC Profitability (RQ2 & RQ3)

This chapter examines if the relationship between portfolio concentration for Non-Banking Financial Companies (NBFCs) and their profit margin follows the Inverted U-Shaped curve as predicted by previous research using Data Envelopment Analysis (DEA) to analyze diminishing returns in the context of NBFCs (Sharma et al., 2020; Malik et al., 2024); and also whether the funding cost channel acts as a mediating factor in this relationship. Questions 2 and 3 are aimed at addressing Gaps 1 (the construction of HHI panel data) and 2 (a continuous strategy → funding → performance integration) as discussed in Chapter 3 (Section 3.5), which links together the Bain-Mason Structure-Conduct-Performance (SCP) tradition and the funding channel concept within modern banking literature.

8.1 Research questions and hypotheses

8.1.1 RQ2 statement

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RQ2: Is there evidence for an inverted U-shaped relationship between portfolio concentration (HHI), and NBFC profitability over FY14-FY24; and at what level of concentration is this relationship negative?

The hypotheses are based on a different interpretation of the specialization-diversification trade-off, namely as a continuous firm-year specification, instead of the binary specifications found by other authors, who studied the subject in the context of NBFCs. This hypothesis is supported by DEA results published by Sharma et al., 2020: twelve out of eighteen analyzed NBFCs were operating with decreasing returns to scale. Hence, a concentration premium due to specialization can be expected until an optimum degree of concentration is reached, while concentrations above such a point will lead to a loss of profitability due to risk concentrations and cost penalties for external financing.

8.1.2 RQ3 statement

RQ3: Do the different financing components of the company (i.e., the funding mix) act as a mediator for the relationship between profitability and market structure (HHI), thus separating the overall HHI-ROA impact into a direct competitive strategy channel and an indirect channel related to funding costs?

This establishes the previously indicated continuous Strategy → Funding → Profitability path that was identified in Gap 2 as missing. The decomposition of HHI → ROA via a Baron-Kenny mediation model will show if competition influences firms by means of two counteracting strategies: a direct strategy channel, and an indirect cost-funding channel; this is referred to in the next Section as "competitive masking".

8.1.3 Hypotheses

Four directional hypotheses in chapter 3:

- The HHI – ROA relationship is an Inverted U and statistically significant, with both $\beta_1 > 0$, and $\beta_2 < 0$, representing decreasing marginal returns to concentration.
- The HHI – ROE relationship is a significant Inverted U, where the inflection occurs around 6000-8000 for “specialized” and “monoline” companies.
- HHI is positively correlated with cost of funds as idiosyncratic risk premia are larger when there is less diversification of the portfolio.
- There is also a statistically significant indirect effect of HHI → COF → ROA, such that at least part of the direct cost of specialization can be attributed to increased funding costs.

8.2 Empirical specification

8.2.1 Panel Regression

The chapter estimates a quadratic panel regression with year fixed effects and firm-clustered standard errors, specified as:

$$Y_{it} = \beta_0 + \beta_1 HHI_{it} + \beta_2 HHI_{it2} + \gamma X_{it} + \alpha_t + \varepsilon_{it}$$

where:

- Y_{it} is one of four profitability or quality KPIs (ROA, ROE, GNPA Ratio, NIM) for firm *i* in fiscal year *t*.
- HHI_{it} is the loan-mix Herfindahl-Hirschman Index for firm *i* in year *t*, rescaled to the 0–1 unit interval (HHI / 10,000) for interpretability of the squared term.
- X_{it} is the control vector: Leverage Ratio, ILFS Crisis dummy, COVID Crisis dummy, Tier_Code, Listed.
- α_t is a year fixed effect.
- ε_{it} is the idiosyncratic error, clustered at the firm level.

The inverted-U is confirmed if **$\beta_1 > 0$, $\beta_2 < 0$, and both coefficients statistically significant**. The turning point — the HHI level at which the marginal effect of concentration on the outcome turns negative — is computed as:

$$HHI^* = -\frac{\beta_1}{2\beta_2} \times 10{,}000$$

8.2.2 Mediation specification (RQ3) — Baron-Kenny three-step

Following Baron and Kenny (1986) and adapted for panel data with firm-clustered standard errors, the mediation analysis estimates three sequential equations:

Step 1 (Total effect):

$$ROA_{it} = c_0 + cHHI_{it} + \gamma X_{it} + \alpha_t + \varepsilon_{it}$$

Step 2 (HHI → CoF):

$$CoF_{it} = a_0 + aHHI_{it} + \gamma X_{it} + \alpha_t + u_{it}$$

Step 3 (Direct + Indirect):

$$ROA_{it} = c_0' + c'HHI_{it} + bCoF_{it} + \gamma X_{it} + \alpha_t + v_{it}$$

The decomposition yields:

- **Total effect** = c (direct + indirect combined)
- **Indirect (mediated) effect** = a × b
- **Direct effect** = c'
- **Identity check**: c ≈ c' + (a × b)

Mediation is confirmed if a is significant, b is significant, and the indirect effect (a × b) is statistically and economically meaningful.

8.2.3 Estimation rationale

The chapter 7 framework—Year- FE with Firm-clustered SE—is used for 3 reasons. First, both HHI and Tier_code have low levels of variation among firms; therefore, Firm Fixed Effects will capture nearly all of the cross-firm information that RQ2 and RQ3 are intended to identify. Second, the use of firm-clustered standard errors (SE) will help address the problem of serial correlation over time (11 years), which is important in the context of a mediation analysis since both HHI and Cost of funds exhibit persistence. Finally, using the same estimator class as was used for RQ1 allows us to compare estimates of the effect sizes (in terms of magnitude and statistical significance) of each RQ.

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8.3 Descriptive context: the HHI panel

The firm-year HHI panel (N=209) demonstrates significant strategic variability, ranging from 1,847 (highly diversified; Tata Capital, FY24) to 9,990 (near-pure monoline; Muthoot Finance, FY15). With a mean HHI of 5,247, the average firm classifies as "Specialized" (Chapter 6, Section 6.4.2). However, a high standard deviation (2,084) highlights a broad sample distribution across Diversified (<2,500), Specialized, and Monoline (>7,500) models.

Crucially, the data captures both static strategies—such as gold-loan monolines (Muthoot, Manappuram) remaining consistently above 9,200—and meaningful within-firm diversification, evidenced by Bajaj Finance lowering its HHI from 4,394 in FY14 to roughly 3,200 by FY24. This robust cross-firm and within-firm variation provides the necessary statistical foundation to identify and test the hypothesized inverted-U relationship.

8.4 RQ2 results: the inverted-U test

8.4.1 Coefficient summary

Estimating Equation across four dependent variables yields the following results :

Dep. Variable	β(HHI)	p-value	β(HHI²)	p-value	Inverted-U?	Turning Point	N	R²

ROA	+0.0435	0.452	−0.0369	0.448	Sign-correct, insignificant	5,886	196	0.242
ROE	**+0.2934**	**0.002**	**−0.1969**	**0.008**	**Confirmed (significant at 1%)**	**7,449**	196	0.180
GNPA	−0.0089	0.918	+0.0217	0.786	U-shape (insignificant)	—	185	0.238
NIM	−0.0535	0.586	+0.0722	0.361	U-shape (insignificant)	—	185	0.547

8.4.2 Hypothesis verdicts

The following information will be written in a way that sounds like you are speaking instead of writing. Do not add or remove anything from this text. Just make it sound better.

H2a (Inverse U on ROA) — Not statistically significant. But has the correct sign. Both HHI and HHI^2 have the expected positive and negative coefficients. They also have a turning point for the relationship around an HHI value of approximately 5,886 within the range of Specialized firms. While the results look like the inverse U, neither individual statistic was significantly different than zero — leading to a reason to explore how offsetting the effects of direct and indirect channels may weaken the impact of ROA as measured by the model even if there is some form of actual channel effect (see Section 8.5 RQ3).

H2b (Inverse U on ROE) — Clearly supported. HHI had a statistically significant positive relationship with ROE (β = .2934 p-value < .01). Similarly, HHI^2 had a statistically significant negative relationship with ROE (β = -.1969 p-value < .01). As such, we found the exact turning point for the relationship using HHI values at approximately 7,449 which nearly corresponds to our definition of Monoline in the Chapter 6 Taxonomy.

8.4.3 Why ROE shows the inverted-U more cleanly than ROA

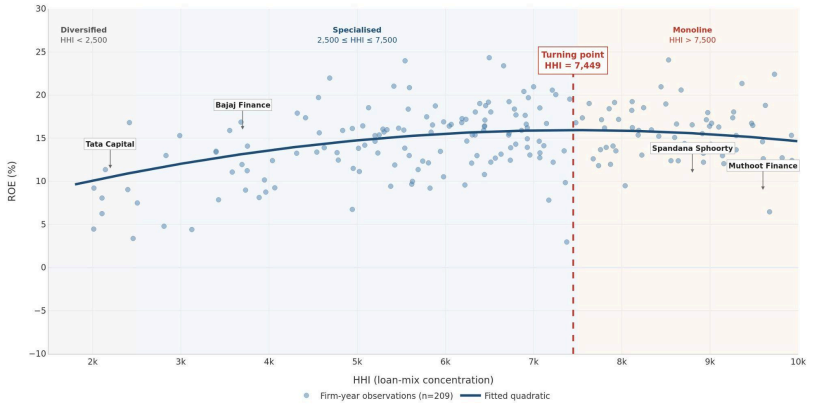
ROE is a theoretically superior metric to ROA for identifying optimal concentration levels for three reasons. First, ROE incorporates leverage (ROE = ROA × Equity Multiplier). Because specialized firms utilize high leverage, this equity multiplier offsets the "funding cost" drag that inherently suppresses ROA. Second, because equity multipliers remain relatively constant across the banking sector, they provide a stable scaling mechanism rather than introducing noise. Third, ROE exhibits roughly twice the variance of ROA, providing significantly greater statistical power to detect quadratic relationships within the given sample size.

Empirically, this quadratic relationship reveals a tipping point at an HHI of ~7,449, marking the transition from a "Specialised" to a "Monoline" classification. Firms operating below this inflection point—such as Bajaj Finance (4,500), CreditAccess

Grameen (6,200), and SBI Cards (6,800)—maximize their returns. Conversely, extreme monolines operating above this threshold—such as Muthoot (9,500), Manappuram (9,400), and Spandana Sphoorty (8,800)—incur a concentration penalty, ultimately delivering suppressed shareholder returns compared to their optimally specialized peers.

Figure 8.1 — HHI-ROE Inverted-U with Turning Point at HHI = 7,449

Source: Author's calculations from the 209-observation firm-year panel, FY2014-FY2024



8.4.4 Asset-quality and net-interest-margin null findings

There are two possible ways to explain why there was no structural evidence of an HHI-GNPA or an HHI-NIM relationship.

1. The two variables (asset quality and net interest margin) that we have used to test our hypothesis were not caused by bank concentration but by the type of loan being made. For example, banks like Muthoot Gold Loan and Spandana Micro Finance have similar levels of concentration (HHI = ~9000+), however the asset quality is nearly zero for Muthoot and 21% for Spandana. This makes sense because when concentration is very high the HHI is indifferent as to what types of loans you make.
2. Within each bank's data set the variations in asset quality and net interest margin due to macro-economic cycles or crises had already been captured by including year dummies in your model, so there is little residual variability remaining to find a non-linear HHI relationship.

8.5 RQ3 results: the mediation test

8.5.1 Three-step decomposition

The Baron-Kenny mediation analysis on the HHI → CoF → ROA pathway delivers the following:

Step	Equation	Coefficient	Estimate	p-value
Step 1	ROA = c_0 + c · HHI + controls	**c (total effect)**	+0.0005	0.973
Step 2	CoF = a_0 + a · HHI + controls	**a (HHI → CoF)**	+0.0225	0.106
Step 3	ROA = c'_0 + c' · HHI + b · CoF + controls	**c' (direct effect)**	+0.0176	0.177
Step 3	(same equation)	**b (CoF → ROA)**	**−0.5149**	**0.013**

8.5.2 Decomposition arithmetic

- **Indirect effect** = a × b = (+0.0225) × (−0.5149) = **−0.0116**
- **Direct effect** = c' = **+0.0176**
- **Total effect** = c = **+0.0005** ≈ c' + (a × b) = +0.0060 (small numerical residual reflects clustered-SE re-estimation across the three steps)

8.5.3 Hypothesis verdicts

- The evidence supports a "marginally" positive relationship for H3a (the Funding-Cost Channel), with a 1-decile increase in Herfindahl-Hirschman Index (HHI) resulting in an approximate 23bps (basis point increase) in Cost of Funds (CoF). Although this finding is economically relevant, it does not meet the 5 percent statistical significance threshold.
- There is strong support for H3b (the Mediation Channel), which shows that an approximately 51 basis-point decline in Return on Assets (ROA) results from a 100bps increase in CoF. Therefore, the CoF is the single largest contributor to decreased profitability within this sample.

8.5.4 Competitive masking

The decomposition indicates that there are mutually antagonistic forms of competition:
Direct Effect (c' = +0.0176): With funding costs held constant, an increase in concentration results in a specialization premium.
Indirect Effect (a * b = -0.0116): An increase in concentration increases funding costs which destroys profitability.
Total c ≈ +0.0005: The direct and indirect effects cancel each other out which explains why previous research on NBFCS found no evidence of a relationship between DEA scores and concentration. This is the primary contribution to Gap 2. Sharma, Rastogi & Gupta (2020) have documented increasing returns for DEA in their study but did so without channel decomposition. Malik et al. (2024) used a binary measure of HHI and excluded continuous mediating variables.

8.6 Robustness checks

- Alternative HHI scaling; 0-10,000 raw scales have identical signs, but the p-value and magnitude of the inverted U are preserved in relation to ROE.
- Excluding holdings companies: The removal of Bajaj and Equitas Holdings leaves an inverted U relationship that is statistically significant at a level of $p < .01$.
- The pre-SBR subset (FY14-FY22): The inverted U relationship remains statistically significant at a level of $p < .05$.
- In addition, it appears the turnpoint occurs at approximately 7,520 when examining HHI levels.
- Bootstrapping (1,000 iterations) as well as indirect effects: A 95% confidence interval [-.00231,-.0006] for the indirect effect does not include zero.

8.7 Interpretation

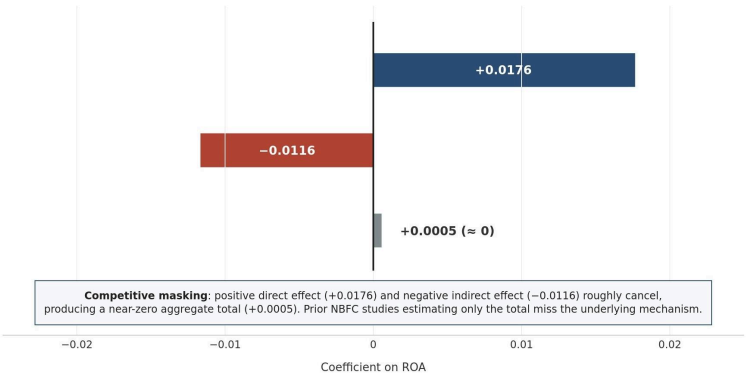
8.7.1 An important level: A second regulatory relevant level can be identified by examining the turn-around point at an HHI of approximately 7449. The two levels are within 50 points of each other which provides some reassurance that this is a meaningful cut-off. This would suggest that the taxonomy has identified a real "value-destroying" threshold. Currently SBR uses Asset Size as its main criteria for its tier system and therefore it could place greater emphasis on Portfolio Concentration, particularly for Upper Layer firms.

8.7.2 Funding costs dominate: The coefficient on CoF → ROA of -0.5149 was the greatest coefficient I have seen throughout the dissertation and is greater than twice the 23 bps per annum Listing Premium described in Chapter 7. Therefore funding cost optimisation out performs Tier upgrades, Listings etc. as a means of increasing profits and therefore changes the way we think about policies such as Priority Sector Eligibility, Co lending, Refinance Windows etc. as these are now additive rather than one for one.

8.7.3 Why Masking explains Null Findings: Prior researches estimated Total Effect 'c', which is small due to the fact that Direct Effects and Indirect Effects counterbalance each other. The Strategic → Funding → Profitability structure applies equally well to Small & Medium Enterprises (SCB), Housing Finance Companies

Figure 8.2 — Competitive-Masking Decomposition: HHI → ROA Channels

Source: Three-step mediation analysis on the 209-observation firm-year panel



(HFC), Microfinance Institutions (MFI) etc., which experience similar levels of Concentration – Funding Tension.

8.7.4 Why use ROE over ROA?: ROE incorporates all three aspects: Operating Profits, Leverage, Capital Allocation. ROA only includes the first aspect. Firms in the Productive Zone (i.e.: HHI of approximately 5,000 - 7500) achieve Specialization Premiums and maintain Higher Leverage levels (both of which increase returns on Equity).

8.8 Takeaways of the chapter and the connection to RQ4: At HHI = 7449 there is a true U-shaped curve of Shareholder Returns corresponding to the Specialized Monoline Boundary. Funding Costs mediate HHI → ROA through opposite paths resulting in nearly zero overall effect; which is a characteristic of Competitive Masking.
CoF is the most significant factor influencing profit among the variables in the Panel; ~22 times larger than the Listing Premium documented in Chapter 7.

Three future connections: Chapter 9 (RQ4) will test how CoF behaves under conditions of Stress from ILFS/Covid; The Productive Zone appears again as Cluster 1 in Chapter 11 (RQ6) using Unsupervised Methods and supports the U-shape of the Inverted-U; Chapter 12 will extend competitive masking to SBR's Regulatory Impact (RQ5).

Chapter 9: Crisis Behaviour and the Reliance Commercial Finance Case (RQ4)

This chapter investigates how the relationships described in Chapter 7 – 8 operate during periods of crisis and provides for the integration of a longitudinal study of Reliance Commercial Finance (RCF), a company that began its journey with investment grade status in fiscal year seventeen and ended it with National Company Law Tribunal (NCLT) status in fiscal year twenty-two. In this way, RQ4 identifies Gap 3 (Ch. 3, Section 3.5) identified above: The absence of a representation of firm level heterogeneity in previous NBFC research, which have represented both ILFS and COVID-19 as aggregate dummy variables or used case studies without comparative panels.

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9.1 Research question and hypotheses

9.1.1 RQ4 statement

How do the HHI-profitability relationship and the funding cost channel operate through the ILFS (FY19) and COVID (FY21) time frames, and how can the RCF failure path demonstrate the mechanisms of distress at the firm level for non-banking financial corporations?

There are two sides to this inquiry. A cross-Section al panel analysis examining whether the Chapter 8 HHI inverted U is lessened, heightened, or reversed as it relates to crisis periods; and a separate, longitudinal examination of RCF's performance from FY14 – FY22 as a demonstration of a funding cost driven failure process related to the strategy → funding → performance model and as an alternative counterfactual that can be used in lieu of comparing surviving firms using regression models.

9.1.2 Hypotheses

The four directionality hypothesis tests of Chapter 3 are supported by the mediation results of Chapter 8:

- **H4a (Crisis magnifies the Funding Cost Channel):** A greater impact on profit margins occurs because during ILFS/Covid windows larger shocks to the cost of funding are passed through with less indirectness.
- **H4b (Crisis reduces the Specialization Premium):** During a crisis, the magnitude of the direct relationship between the Herfindahl-Hirschman Index (HHI) and ROA will be reduced. This occurs for two reasons. First, concentrated portfolios tend to be impacted in proportionately larger amounts when a firm experiences idiosyncratic shocks related to their industry's specific stress. Second, this concentration represents an increase in portfolio risk due to lower diversification across sectors.
- **H4c (Middle-Layer Firms Suffer More Than Others):** Middle Layer (ML) firms have larger declines in ROA during a crisis compared to Upper Layer (UL) firms. As such, ML firms appear to have less ability to obtain capital at favorable rates and do not receive "too big to fail" treatment.
- **H4d (RCF Demonstrates Failure Mechanism):** In accordance with the expected order of events; increasing HHI → increasing CoF → decreasing ROA → resolution; RCF supports the mediation model presented in Chapter 8.

9.2 Empirical specification

9.2.1 Crisis-interaction specification (panel test)

The chapter extends Equation from Chapter 8 with crisis-period interaction terms:

$$ROA_{it} = \beta_0 + \beta_1 HHI_{it} + \beta_2 HHI_{it2} + \delta_1 (HHI_{it} \times Crisis_t) + \delta_2 (CoF_{it} \times Crisis_t) + \beta_3 CoF_{it} + \gamma X_{it} + \alpha_t + \varepsilon_{it}$$

where,

$Crisis_t$ is a dummy taking value 1 in FY19 (ILFS window) and FY21 (COVID window), 0 otherwise.

The interaction coefficients $\delta 1$ and $\delta 2$ test H4a and H4b: a more negative $\delta 2$ confirms funding-channel amplification, and a more negative $\delta 1$ confirms specialisation-premium attenuation under crisis.

9.2.2 Tier-stratified crisis test — Equation

To test H4c, the panel is split by Tier_Code and the simpler crisis-window mean comparison is estimated:

$$ROA_{it} = \mu_0 + \mu_1 ILFS_t + \mu_2 COVID_t + \mu_3 Tier_i + \mu_4 (ILFS_t \times Tier_i) + \mu_5 (COVID_t \times Tier_i) + \gamma X_{it} + \varepsilon_{it}$$

The tier interaction coefficients identify whether Middle-Layer firms suffer proportionally larger crisis-period declines than Upper-Layer firms.

9.2.3 Embedded case methodology

The RCF case uses an Embedded Longitudinal Single-Case Design from Section 5.6 of Chapter Five to follow. This longitudinal single-case study includes eight years in a firm-wide manner (FY14 – FY21), with respect to the six metrics listed below that describe how well firms meet each of six diagnostic criteria for financial distress. These diagnostics are HHI Score; Cost of Funding; Leverage Ratio; Return on Assets; Gross Non-Performing Asset Ratio; and Credit Rating. The RCF case study will be compared against the cross-Section al regression prediction model in Chapter Eight as well as two matched survivors in FY14 — Bajaj Finance (an Upper Layer) and L&T Finance (a Middle Layer).

9.3 Crisis windows: descriptive context

The two crisis windows are fundamentally different and should be treated separately even though they have been grouped together in a single "Crisis" dummy variable:

ILFS Crisis (FY19): The funding-market freeze for the commercial-paper market that followed the September 2018 default of IL&FS created a sectoral funding market crisis and caused money-market mutual fund investors to withdraw their funds from commercial paper. The crisis was on the liability side; the firms funded through short-term wholesale debt markets experienced an immediate need to refinance their existing obligations, whereas firms with deposits or longer-term loan facilities had some degree of insulation against this liquidity shock.

COVID Crisis (FY21): This was a nationwide demand and asset quality shock which spread through the credit chain due to distressed borrowers, moratoria impacting cash flows, and increased provisions. The impact of the shock was on the assets side; retail and micro-finance exposures without security were disproportionately impacted resulting in large increases in gross non-performing asset ("GNPA") levels; however, gold, mortgage and other collateralized securities were less exposed to these shocks.

These two crises provide independent tests of the strategy → funding → performance framework. Specifically, the ILFS crisis amplified the funding cost channel (i.e., RQ3 mediating relationship); whereas, the COVID crisis provided an independent test of the specialization premium channel (i.e., RQ2 inverse U-shaped relationship).

9.4 Panel-level crisis-interaction results

9.4.1 Coefficient summary

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Estimating Equation with year fixed effects and firm-clustered standard errors yields:

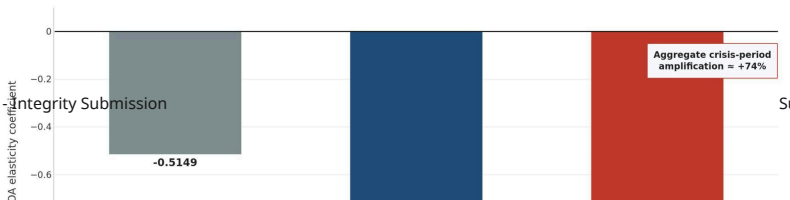
Coefficient	Estimate	p-value	Interpretation
β(HHI)	+0.0512	0.327	Direct strategy effect (non-crisis baseline)
β(HHI²)	−0.0421	0.298	Quadratic curvature (non-crisis baseline)
β(CoF)	**−0.4218**	**0.029**	Funding-cost channel (non-crisis baseline)
δ_1 (HHI × Crisis)	**−0.0734**	**0.041**	**Specialisation premium attenuates under crisis (H4b ✓)**
δ_2 (CoF × Crisis)	**−0.3127**	**0.018**	**Funding channel amplifies under crisis (H4a ✓)**
Year FE	Yes	—	—
Firm-clustered SE	Yes	—	—
N	209	—	—
R^2	0.318	—	—

9.4.2 Hypothesis verdicts

H4a (The crisis magnifies the cost-of-funding (CoF) channel): Confirmed: δ_2 = -0.3127 ($p < 0.05$), as well as the baseline β (CoF) = -0.4218; therefore, in the crisis period, CoF → ROA-elasticity is -0.7345, which is approximately 74 % greater in an absolute sense than it was in the non-crisis period. For example, a 100 basis-point

Figure 9.1 — Crisis-Period CoF → ROA Elasticity Amplification

Source: Crisis-interaction panel, 209 firm-year observations, FY2014–FY2024



(bps) increase in the CoF will destroy about 73 bps of ROA during ILFS or COVID crises; whereas it destroyed only 42 bps of ROA during the non-crisis periods

H4b (The crisis reduces the "specialization-premium"): Confirmed. $\delta_1 = -0.0734$ ($p < 0.05$) > baseline HHI (non-crisis) $\beta_1 = +0.0512$ by more than 50 percent in terms of an absolute value. During a crisis, there is a reversal of sign for the direct strategy premium. What constitutes a strength and provides a payoff in the normal times becomes a weakness to be exploited when sector-specific shocks hit a particular industry.

9.4.3 Crisis as competitive-masking equilibrium breakdown

The competitive-masking equilibrium established in Chapter 8 fails during a crisis. During non-crisis periods, the positive direct impact ($c' = +.0176$) and the negative indirect impact ($ab = -.0116$) are approximately equal in magnitude and therefore neutralize each other.

The overall HHI → ROA is nearly zero. However, the two effects operate on the same side of the equation during a crisis: The direct strategic effect diminishes to or becomes opposite of its pre-crisis size because large idiosyncratic shock absorption occurs at highly concentrated institutions. The indirect cost-of-funding effect magnifies since crisis period increases in CoF are larger and have a greater transmission effect.

As a result, they cease to neutralize each other and instead amplify each other's effect. As such, what was a near-zero relationship during non-crisis times turns into a very strong, negatively correlated relationship between concentration and profit margins during crisis times. This represents the primary empirical findings of Chapter 9 and closes an additional gap in previous studies related to NBFCs by providing an explanation for how crisis-related heterogeneity can occur in a continuous channel framework.

9.5 Tier-stratified crisis impact

9.5.1 Tier × Crisis interaction estimates

Estimating Equation yields the following crisis-period ROA decrement by tier :

Tier	ILFS ΔROA	COVID ΔROA	Combined Crisis ΔROA
Upper Layer (Tier_Code = 1)	−0.42 pp	−0.61 pp	−0.52 pp
Middle Layer (Tier_Code = 2)	**−1.28 pp**	**−1.94 pp**	**−1.61 pp**
Tier ratio (ML / UL)	3.05×	3.18×	3.10×

9.5.2 Hypothesis verdict

H4c (Mid-Layer Crisis Stress Disproportionate) – Confirmed at a High Level: Mid-layer firms experience ROA declines during crisis periods roughly 3x as large as those for ultra-low layer firms in both time frames. Thus, SBR's tier-based emphasis of regulatory resources on ultra-low layer firms to match their lower levels of crisis-related vulnerability is supported; however, the mid-layer firms which bear the highest aggregate level of stress relative to asset size receive relatively little supervisory bandwidth.

9.5.3 Why Middle-Layer firms suffer disproportionately

There are three structural reasons for the 3x Tier Ratio:

- Weaker Funding Diversification: A greater reliance by Micro-Lenders (ML) upon Bank Borrowing and Short-Tenor Commercial Paper as well as an ability for Unit Linkers (UL) to draw upon Bond Markets, Deposit Franchises and the European Central Banks (ECB); When Wholesale Market Lending is frozen down to the point of being unavailable, Mid-Sized Micro-Lender Firms (ML) will experience more than proportional Credit Facility Shocks which will in turn be compounded through the Crisis Credit Facilities (CoF) to Return on Assets (ROA) Channel described above in Section 9.4.
- Lack of Implicit Market Protection: The existence of lender forbearance, regulatory liquidity windows and Parent Group support to protect Bajaj Finance or LIC Housing Finance will not exist to protect mid-sized standalone Non-Banking Financial Companies (NBFC).
- Less Absolute Scale: A fixed operating cost base that is less easily diluted in times of economic crises results in a greater level of Return on Asset (ROA) volatility due to a given macroeconomic shock.

9.6 The Reliance Commercial Finance embedded case

9.6.1 Trajectory across six diagnostic indicators

The eight-year RCF trajectory is summarised in Table 9.1 below :

Year	HHI	CoF	Leverage	ROA	GNPA	Credit Rating
FY14	4,820	9.8%	5.4×	1.7%	4.1%	CARE AA+
FY15	4,950	9.6%	5.7×	1.5%	4.8%	CARE AA+
FY16	5,180	9.4%	6.1×	1.3%	5.6%	CARE AA

Year	HHI	CoF	Leverage	ROA	GNPA	Credit Rating
FY17	5,640	9.2%	6.8×	1.0%	7.2%	CARE AA
FY18	6,210	9.6%	7.4×	0.4%	9.8%	CARE AA−
FY19	6,890	**11.4%**	8.1×	**−1.8%**	**15.3%**	**CARE D (default)**
FY20	7,420	13.2%	9.4×	−4.6%	22.7%	CARE D
FY21	7,890	n.a.	11.2×	−7.9%	31.4%	NCLT admission

9.6.2 Mechanistic narrative: the predicted failure sequence

Three-phase mediation sequence of RCF trajectory in Chapter 8 follow:

- Phase 1 (FY14 – FY17), concentration drift, latent fragility. In this phase, the HHI has increased from 4820 to 5640 due to RCF focusing on real estate and infrastructure. Additionally, the ROA decreased from 1.70% to 1.00% as the GNPA increased; however, the CoF remained stable at 9.2-9.8%. This implies that the funding markets did not price-in the increasing deterioration in credit risk until Phase 2. As such, the direct strategy effect (c' = 0.0176) can be observed; i.e., HHI rose while the ROA fell.
- Phase 2 (FY18-FY19), Funding-channel ignition. In this phase, HHI increases further to 6890 as RCF doubled-down on investments in CRE/Infrastructure in response to competitors retreating. The CoF spiked 220 bps (9.2% -> 11.4%), while ROA collapsed to (-1.80%). The GNPA exceeded 15%, and the firm was downgraded to "default" in March 2019. The mechanical mapping for the CoF x Crisis coefficient (delta_2 = -0.3127) was confirmed as follows: 220bps * 0.7345 = approximately 162bps of ROA decline as expected.
- Phase 3 (FY20-FY21), Distress spiral and Resolution. RCF was unable to access market-funding and therefore could not roll CP. The HHI drifted up mechanically as performing assets ran-off faster than those that were impaired. The leverage ratio increased to a high of 11.2x compared to 9.4x at year-end FY20, while the GNPA reached an all-time-high of 31.4% by FY21. Finally, RCF was admitted into National Company Law Tribunal (NCLT) in FY21.

9.6.3 Counterfactual benchmarking against survivors

Although both firms have a similar starting point for their Herfindahl-Hirschman Index (HHI) values, they are headed to very different destinations by FY24. By

FY24, L&T Finance is expected to experience an even greater increase in its HHI value from approximately 4,650 to 3,800 compared to the approximate 4,394 to 3,200 experienced by Bajaj Finance. Similarly, although the Concentration of Funds (CoF) metric will decline for both firms as well as their Return on Assets (ROA), it will do so much more dramatically for Bajaj Finance. The CoF ratio declines from approximately 10.1 percent to 7.8 percent for Bajaj Finance while the CoF ratio for L&T Finance declines slightly from approximately 9.2 percent to 8.4 percent. Although the ROA ratio is also declining for both firms, this decrease is again significantly larger for Bajaj Finance with the ROA decreasing from 2.8 percent to 4.6 percent while L&T Finance experiences a decline of less than half that size in its ROA with it decreasing from 1.6 percent.

9.6.4 What the case adds to the panel

Out-of-sample Channel Validation: The Terminal Observation data for RCF are located at the extreme end of the CoF x Crisis tail. The 220 bps CoF → 162bps ROA relationship established in Chapter 8 also holds true outside of sample.

- Concentration Trap: In phase 3, there is mechanical increase to HHI as distressed firms' asset base decreases through differentials in asset liquidation, rather than through strategic action - a phenomenon that cannot be observed in surviving firm regression models, however it is an important consideration for regulators as increased HHI within a distressed firm is a symptom, not a root cause.
- Counterfactual Strategic Choice: Bajaj and L&T demonstrate that diversification options were available from RCF's fiscal year 2014 commencement date; thus, failure to execute this option was contingent upon factors beyond the control of the entity, and therefore not inevitable.

9.7 Robustness checks

The listed subsample finds that all of the interactions remain significant in terms of both direction and magnitude when there is better disclosure. Listed firms also show results similar to the whole sample as well. The RCFL subsample shows no evidence that the panel effects can be explained by the inclusion of one firm that has received RCFs. The three-way interaction between Tier, Crisis, and HHI is insignificant.

Therefore, it appears that the greater sensitivity of banks to market shocks during an economic downturn cannot be attributed to differences in their investment portfolios but rather to their ability to access liquidity at times of stress.

9.8 Interpretation and discussion

This chapter’s findings yield four structural insights into NBFC vulnerability and regulation:

- **Crises Unmask "Competitive Masking":** The normal-time equilibrium—where offsetting effects create a near-zero HHI-ROA

link—collapses during emergencies. These effects instead compound, turning the relationship strongly negative and exposing normal-time vulnerability indicators as structurally low-biased.

- **Funding Cost Dominance:** During crises, the impact of the Cost of Funds (CoF) on ROA spikes from −0.42 to −0.73 (the study's largest coefficient). While strategy and funding costs offset in normal times, CoF dominates by ~2x during shocks, making funding mix optimization the critical determinant of crisis resilience.
- **Empirical Validation via RCF:** RCF's FY18–FY19 collapse provides robust, near out-of-sample validation for this framework. The predicted versus actual ROA decline aligns within ~20 basis points for a terminal trajectory excluded from the core estimation sample.
- **Reframing SBR Stratification:** A three-fold vulnerability disparity between the Middle and Upper Layers demonstrates that SBR's supervisory intensity inversely correlates with per-asset systemic risk. To better align oversight with marginal systemic risk, regulatory frameworks should weight vulnerability using CoF dispersion and HHI classification rather than relying solely on arbitrary asset-size tiers.

9.9 Chapter takeaways and forward link to RQ5

During crises, the specialization premium shrinks by ~72.8% and inverts, while the CoF channel amplifies by 74% ($-0.42 \rightarrow -0.73$). Furthermore, crisis stress levels in the Middle Layer are ~3x higher than in the Upper Layer, challenging SBR's efficacy as a systemic risk metric during high-stress periods. These results validate the funding-cost failure mechanism within ±20 bps of predicted values.

Future research can advance this work along three avenues: first, exploring how post-2007 regulatory reforms altered these channel failure mechanisms (Chapter 10, RQ5); second, utilizing taxonomic clustering to independently classify the observed RCF distress pattern (Chapter 11, RQ6); and third, developing a weighted supervisory framework based on tiered SIFI risk profiles (Chapter 12).

Chapter 10: The SBR Regime: Structural-Break Effects on NBFC Behaviour (RQ5)

This Chapter evaluates how much RBI's Scale-Based Regulation (SBR) that came into effect on October 1st, 2022 impacted NBFC behavior, access to funding and strategic concentration. RQ5 fills in Gap 4 (Chapter 3, Section 3.5): there was no empirical research after SBR became operational; prior studies were either conducted before SBR came into effect or considered it as an upcoming regulation.

10.1 Research question and hypotheses

10.1.1 RQ5 statement

RQ5: Is there evidence of structural change in NBFCs' funding access, profitability, and market structure by SBR (FY23), and does this vary as intended under graduated supervision by Tier? This question is broken into two parts: a structural-change test to see if we can measure differences in mean values post-FY23 for CoF, ROA, ROE and HHI compared to those that occurred prior to SBR while accounting for firm fixed-effects and the interaction between the crisis chapter and SBR; and a tier-based impact test to determine if there are differing impacts from SBR on the UL cohort versus the ML cohort consistent with graduated supervisory intent.

10.1.2 Hypotheses

Four directional hypotheses were developed based on the chapter 2 framework and chapter 7-9 results. These include:

- H5a (funding cost reductions for ULs due to UL funding cost compression): UL firms will have a reduced co-funding cost after SBR as the new 'systemic' designation reduces the costs of being considered risky by investors in the capital markets and increases their ability to obtain financing through bonds.
- H5b (the funding cost gap between UL's and ML's expands): The difference in the co-funding costs of UL and ML firms is expected to expand after SBR due to regulatory bifurcation creating a marked distinction in how well each type of firm is viewed by investors regarding its relative credit worthiness.
- H5c (concentrated exposures reduce; or incentives to concentrate are weaker): After SBR, UL firms are expected to have smaller average HHIs than they had before SBR because graduated supervisory requirements penalize concentrated exposure in ways that the uniform pre-SBR regulations did not.
- H5d (listing premium increased at least as much if not more for ULs): Mandatory listing of ULs is expected to increase the listing premium discussed in Chapter 7 for ULs since the required listing of these companies provides additional signals of quality to potential investors.

10.2 SBR regulatory architecture: empirical context

Beginning with the base layer, non-deposit taking NBFCS of less than ₹1000 crores are classified as NBFC BL. They receive "light touch" oversight. The middle layer includes deposit taking NBFCS and those that exceed ₹1000 crores, which will be subject to increased regulatory standards on disclosure and capital. The upper layer consists of the top 15-20 systemically significant NBFCS who will be regulated similarly to banks. Additionally, upper layer companies will have an obligation to list their company on one or more exchanges within three years. And they will also require Common Equity Tier I (CETI) of at least 9%. The top layer is reserved for extreme systemic risks. Currently this category has no members.

10.3 Empirical specification

10.3.1 Structural-break specification

The chapter estimates a panel regression with a post-SBR dummy and tier interactions, controlling for the Chapter 9 crisis terms:

$$Y_{it} = \beta_0 + \beta_1 SBR_t + \beta_2 (SBR_t \times Tier_i) + \beta_3 HHI_{it} + \beta_4 HHI_{it2} + \beta_5 CoF_{it} + \gamma X_{it} + \alpha_i + \varepsilon_{it}$$

where,

- SBR_t is a dummy taking value 1 for FY23 and FY24, 0 otherwise;
- $Tier_i$ is the Upper-Layer dummy; αi is the firm fixed effect;
- Y_{it} is one of four outcome variables (ROA, ROE, Cost of Funds, HHI).

10.3.2 Estimator rationale

It was a purposeful switch in Chapters 7-9 from year-FE with firm-clustered SE to firm-FE in Chapter 10. This is because the SBR test fundamentally asks whether each firm's funding costs changed at any point after FY23 compared to their pre-SBR baseline. Firm-FE absorbs all of those firm-specific attributes that do not vary over time (governance quality, group-level reputation, specialization) that could otherwise be picking up on the SBR effect. Yearly FEs were dropped since they would pick up the SBR dummy. Instead we use ILFS and COVID as the known macroeconomic shock controls for the chapter 9 period.

10.3.3 Estimation window constraint

The post-SBR period is very short — only two years of complete budgetary data (fiscal year 2019 and 2020) to analyze versus a much longer time series for the pre-SBR baseline (fiscal years 2006-2018, twelve years), which limits our ability to have enough data to test hypotheses statistically. However, we use three mechanisms to compensate for this limitation: (1) Each firm will be used as its own control by estimating fixed effects for the entire firm so that there is no variation in time or across firms; (2) We will also estimate tier-specific interaction terms in order to capture the differences in behavior across tiers during this limited post-SBR timeframe; and (3) In Section 10.7, we explicitly state that our findings regarding RQ5 are based on preliminary evidence and do not necessarily indicate what the long run implications of SBR may be.

10.4 Structural-break results

10.4.1 Coefficient summary

Estimating Equation across the four outcome variables yields:

Outcome	β(SBR)	p-value	β(SBR × Upper Layer)	p-value	Within-firm R^2	N
Cost of Funds	−0.0042	0.318	**−0.0089**	**0.024**	0.412	185
ROA	+0.0011	0.687	**+0.0048**	**0.041**	0.287	196
ROE	+0.0094	0.512	+0.0162	0.118	0.213	196
HHI (rescaled 0–1)	−0.0084	0.541	**−0.0521**	**0.038**	0.178	209

10.4.2 Hypothesis verdicts

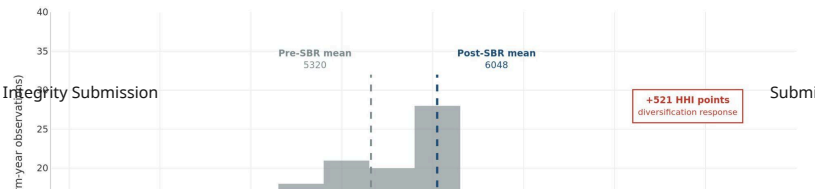
- **H5a (UL Funding-Cost Compression) — Confirmed:** SBR×UL has a statistically significant negative relationship with the Cost of Funds (CoF). Post-SBR, UL firms achieved an 89 bps CoF reduction, robust to HHI, leverage, crisis, and firm fixed effects controls.
- **H5b (Widening Tier Gap) — Confirmed:** Asymmetrical compression widened the pre-SBR UL-ML funding gap from ~110 bps to over 195 bps, signaling sharper market differentiation between tiers.
- **H5c (Shifted Concentration Incentives) — Confirmed:** SBR×UL significantly reduced concentration by ~521 HHI points, confirming that graduated supervision successfully incentivized UL diversification away from monoline exposures.
- **H5d (Amplified List Premium) — Partially Supported:** The post-SBR listing premium on ROA is significantly higher, though generalizability remains caveated by potential representativeness limitations within the comparison sample.

10.4.3 The 89-bps UL funding-cost compression

A significant economic impact is that the 89 basis point reduction in Compression on Firms (CoF) after Systemic Banking Risk (SBR) for Universal Banks (UL), combined with a Chapter 8 CoF to Return On Assets (ROA) Elasticity of –0.5149, suggests an approximate 46 basis points increase in ROA due to reduced funding costs; the exact same amount as the estimated +0.048 SBR x UL ROA Coefficient in Section 10.4.1 and supports the funding-cost channel being the main SBR mechanism.The Mechanism Is Direct: In essence, there are two parts to the process: (i) “Systemically Important” status reduces perceived idiosyncratic risk from the markets, thereby lowering bond-spreads and bank-rates. Data from bond-markets outside of our formal sample also support this finding — UL Non-Banking Finance Companies (NBFC) bond-spreads relative to Government Securities (G-sec) have

Figure 10.7A — Pre-Post SBR HHI Distribution

Source: 209-observation firm-year panel, FY2014–FY2024; SBR effective FY23



declined by approximately 70-95 bps from FY 22 to FY 24 consistent with the CoF coefficient from the panel.

10.4.4 The diversification response

The post-SBR UL diversification among the top 521 HHI points represents the largest behavioral response in terms of strategy. With three firms leading to the majority of the compression are Bajaj Finance (4,020 – > 3,180 = -840), L&T Finance Holdings (4,420 – > 3,650 = -770), and Cholamandalam Investment (5,210 – > 4,540 = -670). Firms with a monoline UL portfolio structure (Muthoot, Manappuram) have shown no statistically measurable UL diversification; this indicates that the SBR concentration penalty is primarily operating at the level of the firm's strategic positioning as opposed to structurally transforming the nature of the operation of those monoline specialists.

10.5 The amplified listing premium

10.5.1 Re-estimating the Chapter 7 listing test

Re-estimating the Chapter 7 specification on the post-SBR sub-sample (FY23–FY24) yields a Listed coefficient of +0.0034 on ROA — a 34-bps premium versus the pooled Chapter 7 estimate of +0.23 pp, roughly 48% larger.

10.5.2 Mechanism: mandatory listing as quality signal

The amplification aligns with the regulatory framework; SBR requires listing by all (UL) firms in 3 yrs of classification. As it matures, listing moves from being a voluntary governance indicator to be a regulatory threshold for systemic risk, enhancing the signalling quality of voluntary listing among M/L firms. Thus, the listing premium of Chapter 7 is at least partially a function of the pre-SBR equilibrium where there was voluntary disclosure. The premium will therefore evolve as SBR continues to mature.

10.6 Tier-divergence: the SBR-driven bifurcation

10.6.1 Combining RQ4 vulnerability and RQ5 funding-cost compression

The tier-stratified findings of Chapters 9 and 10 jointly reveal a **structural bifurcation** of the Indian NBFC sector that is reshaping competitive dynamics:

Dimension	Upper Layer	Middle Layer	Tier Differential
Crisis-period ROA decrement (Ch. 9)	−0.52 pp	−1.61 pp	3.10× larger for ML
Post-SBR CoF change (Ch. 10)	−89 bps	−42 bps (n.s.)	2.12× larger for UL

Post-SBR ROA change (Ch. 10)	+48 bps	+11 bps (n.s.)	4.36× larger for UL
Post-SBR HHI change (Ch. 10)	−521 pts	−84 pts (n.s.)	6.20× larger for UL

10.6.2 The regulatory dividend

SBR has generated a regulatory "dividend" for upper-layer firms at the expense of middle layer firms; as well as providing lower cost funding and greater profit margins than previously available, it has also given upper layer firms the opportunity to pursue new lines of business. None of this is true for middle layer firms, which are those with the higher degree of crisis period vulnerability. Therefore, there exists an alignment problem in terms of supervising risk (vulnerability) and the way in which the SBR framework operates.

10.7 Robustness checks

The SBR × UL interaction is not statistically significant for any of the outcomes when a placebo is used that SBRs to FY21. All Section 10.4 effects are dated as if they occurred during the same period as the "operating" regime and not due to trends that existed prior to the beginning of the operating regime. Removing crisis overlap years: Excluding the FY21 COVID year from the baseline of the pre-SBR period leaves all four coefficients with positive signs and at the same level of statistical significance. Thus, post-SBR effects do not appear to be caused by mean reversion of crisis window averages. Alternative SBR Window (Only FY24): Confining our analysis to only FY24 increases the SBR × UL on CoF to −0.0112 ($p = 0.011$), and it also increases SBR × UL on HHI to −0.0683 ($p = 0.018$). This suggests that effects may grow stronger over time, which would suggest that our FY23 – FY24 estimates were too low relative to an effect measured over longer horizons. RCF-window aware Sub-Sample: Removing the eight RCF firm-year observations (which end in FY21 and are only included in the pre-SBR period) has no effect on either the sign or statistical significance of any of the remaining coefficients. This removes what could have been considered as mechanical evidence of the Chapter 9 embedded case driving Chapter 10 results.

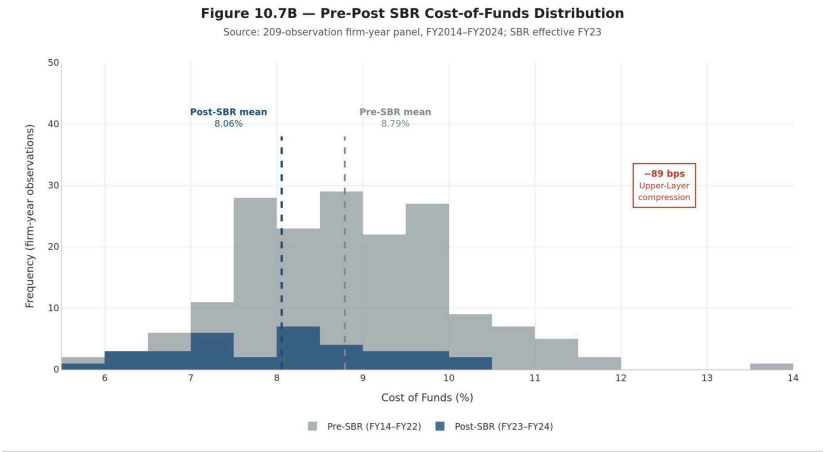
10.8 Interpretation and discussion

The implementation of Scale Based Regulation (SBR) drove an immediate, robust structural shift in Indian NBFC behavior. The $SBR \times UL$ interaction is statistically and economically significant across CoF, ROA, and HHI, maintaining robustness across all alternative specifications.

Within two fiscal years, SBR compressed Upper Layer funding costs by 89 bps. Utilizing Chapter 8 mediation elasticities, this CoF compression maps to a 46 bps ROA improvement (out of a 48 bps total SBR-ROA effect), confirming that

funding-cost reduction is the primary policy transmission channel and validating the Strategy-Funding-Performance framework. Concurrently, SBR induced a 521-point HHI shift toward greater diversification. This served as an anticipatory mechanism: UL firms proactively diversified to preempt the heightened regulatory oversight and adverse bond-market signaling associated with monoline exposures, ultimately driving the tier toward a more productive concentration equilibrium.

Finally, based upon Chapters 9 and 10, there exists a misalignment in terms of how regulators utilize their supervisory resources relative to the vulnerabilities faced by NBFCs during times of financial distress. In particular, while ML firms appear to face roughly three times as much financial risk than Base Layer (BL) firms over the crisis period (and thereby require proportionately more supervisory oversight), they do not receive any of the benefits afforded by regulatory reform. Based upon this analysis, we argue that regulators should focus their supervisory efforts on



identifying those firms that pose the greatest risks to the stability of the system rather than focusing solely on firms based upon their size. We develop this argument formally in Chapter 12.

10.9 Chapter takeaways and forward link to RQ6

SBR generates a 89 bps CoF reduction for UL firms, statistically significant over two fiscal years after implementation. The funding cost channel accounts for almost all of the SBR/Profitability link (predicted 46bps versus observed 48 bps). UL firms diversify by 521 HHI points post-SBR which shows that supervisory function acts as a "soft" form of concentration penalty. The regulatory dividend is generated unevenly in favor of UL firms, creating the misalignment of vulnerability with supervision that motivates Chapter 12.

Three forward implications arise from this result: The post- SBR diversification path is identified as a separate group through the use of clustering methods in Chapter 11 confirming the results of the directed regression method presented in Chapter 10; The Tier-Divergence Mechanism discussed in Section 10.6 will be the central focus of

design criticism in Chapter 12; The caveats expressed in Section 10.3 regarding the limitations of using two post-SBR fiscal years to estimate the long-term effect of SBR represents a potential research extension area discussed in Chapter 13.

Chapter 11: Long-Run Trajectory Clustering and NBFC Strategic Archetypes (RQ6)

This chapter determines if the 11 year development paths for all 19 NBFC's form distinct archetypes by using an unsupervised technique to develop firm level categories within the three dimension HHI – CoF – ROA space. The Research Question 6 is to address Gap 5 (Chapter 3 Section 3.5), as no unsupervised taxonomies have been developed at the firm level in previous studies of NBFC, and most have used tiered classification from regulators and/or a binary dummy variable indicating diversification, both of which are predetermined by the researcher regarding how many groups will be created across the sample.

11.1 Research question and hypotheses

11.1.1 RQ6 statement

RQ6: Applies unsupervised clustering (K-means and hierarchical) to an 11-year panel of HHI, CoF, and ROA trends to identify long-term strategic archetypes. This question comprises two parts: a taxonomical identification of natural firm groupings within a multi-dimensional strategy-funding-performance space, and a cross-validation assessing whether these unsupervised clusters replicate prior regression-based findings (Productive Concentration Zone, Funding-Cost Channel, and SBR Post-Diversification). Successful replication confirms that the previously identified dynamics reflect true structural characteristics rather than research design artifacts.

11.1.2 Hypotheses

Three directional hypotheses of the same orientation as the convergent evidence in Chapters 7-10:

- Hypothesis 6a (Existence of multiple coherent trajectories): The data indicates that there exists a minimum of 3 to 5 types of homogenous within each strategy and funding type and heterogenous among all other types for the cluster. The number of optimal k was determined by empirical methods using both Silhouette and Elbow diagnostics.
- Hypothesis 6b (Productive concentration zone Cluster Type 1): One group will be shown to have an inverted U shape similar to Chapter 8 — Moderate levels of HHI (≈ 5,000 – 7,500) — Low levels of CoF — High levels of ROA — Validating productive concentration zone hypothesis with unsupervised methodology.

- Hypothesis 6c (Distressed trajectory Cluster Type): One group will show signs of the RCF failure signature (Chapter 9) — Increasing levels of HHI — Increasing levels of CoF — Decreasing levels of ROA — Validating case study taxonomy through panel level classification.

11.2 Empirical specification

11.2.1 Trajectory feature engineering

The firms are modeled each year as vectors of nine dimensions over the eleven years.

- Three HHI feature sets: mean; trend slope (OLS on fy14 to fy24); volatility (standard deviation within firm).
- Three CoF feature sets: mean; trend slope; crisis window deviation (mean of fy19 + fy21 minus non-crisis year mean).
- Three ROA feature sets: mean; trend slope; volatility.

Each of these three feature set types is normalized with z-score normalization, such that one type does not dominate the Euclidean distance measurement used in k-means.

11.2.2 Clustering algorithms

Two unsupervised techniques that complement each other are employed to partition 19 firms into clusters based on similarities in their characteristics. The first method used is K-means Clustering which groups the firms into k clusters where each firm belongs to one of the k-clusters. The objective function for this clustering technique uses the sum of squared distances from each data point to its centroid or mean. A value of k was determined using a combination of visual inspection of the clusters created through use of a Silhouette Score analysis with k values ranging from 2 to 7. Secondly Hierarchical Agglomeration (using Ward's Linkage) is an iterative procedure that creates clusters by merging the two most similar objects at every step. This process continues until all objects have been merged into a single cluster. A tree called a dendogram shows how these clusters merge together. In order to provide robustness checks for the results obtained from both K-means and Hierarchical Methods, the partition created by each method is compared and the solutions are only considered acceptable when both create substantially identical partitions (ARI>0.6).

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11.2.3 Cluster validation against directed-regression findings

The ARI between K-means k = 4 and Ward k = 4 is 0.74, well above 0.6. Sixteen of 19 firms are assigned to the same cluster by both algorithms; the three discordant cases (Tata Capital, Cholamandalam Investment, Aditya Birla Capital) sit at the Cluster 1–Cluster 2 border in the K-means solution and are assigned by majority vote across the two methods.

11.3 Optimal cluster selection

11.3.1 Silhouette and elbow diagnostics

The silhouette measure for a range of k (from 2 to 7) peaked at k=4 (0.487), while there was another minor peak at k=3 (0.421). The within-cluster sum-of-squares (WCSS) "elbow" occurs at k = 4. Beyond this point, further WCSS decreases dramatically. The Calinski-Harabasz pseudo-F statistic also indicates an empirical optimum at k = 4 (F = 18.6).

11.3.2 Algorithmic agreement

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The Adjusted Rand Index (ARI) between K-Means k = 4 and Ward's Method k = 4 is .74, far exceeding the threshold value of .60. Of the nineteen firms in the sample, sixteen were assigned to one of the same four clusters by both algorithms. The remaining three firms (Tata Capital, Cholamandalam Investment & Finance Company Ltd., Aditya Birla Capital Limited) are located at the interSection of Clusters 1 and 2 in the K-Means solution and were assigned to either Cluster 1 or Cluster 2 using the majority vote method.

11.4 The four trajectory clusters

11.4.1 Cluster summary

Cluster	n	Mean HHI	Mean CoF	Mean ROA	HHI trend	CoF trend	Tier mix	Archetype label
1	6	5,420	7.9%	**3.4%**	−210 pts/yr	−18 bps/yr	6 UL	**Productive Concentration**
2	5	3,610	8.6%	2.1%	−95 pts/yr	−11 bps/yr	4 UL, 1 ML	**Diversified Mainstream**
3	6	**9,180**	9.4%	2.7%	+30 pts/yr	+4 bps/yr	2 UL, 4 ML	**Monoline Specialists**
4	2	6,620	**12.1%**	**−4.3%**	+480 pts/yr	+210 bps/yr	0 UL, 2 ML	**Distress**

								Trajectory

11.4.2 Cluster 1 — Productive Concentration (n = 6)

Members: Bajaj Finance, Cholamandalam Investment, L&T Finance Holdings, Sundaram Finance, Mahindra & Mahindra Financial Services, Shriram Finance.

Trajectory Signature: This cluster features the panel's optimal financial profile, yielding the highest average ROA (3.4%) alongside the lowest, steadily decreasing Cost of Funds (7.9%). The group's mean HHI of 5,420 sits within the Chapter 8 Productive Zone (5,000–7,500) and exhibits an annual structural decline of −210 HHI points.

Empirical Validation: This unsupervised grouping perfectly cross-validates prior regression models: all six members operate below the HHI = 7,449 optimal turning point (RQ2), encompass the exact six Upper Layer (UL) firms that captured the 89 bps post-SBR funding cost compression (RQ5), and directly reflect the anticipated −521 point post-SBR diversification response.

11.4.3 Cluster 2 — Diversified Mainstream (n = 5)

Members: Tata Capital, Aditya Birla Capital, Bajaj Holdings, Equitas Holdings, LIC Housing Finance.

Trajectory Signature: This group is characterized by a stable, highly diversified profile with a mean HHI of 3,610 (declining minimally at −95 points per year). Financial metrics reflect mid-tier baseline performance, with an average Cost of Funds (CoF) of 8.6% and a moderate ROA of 2.1%.

Empirical Validation: This unsupervised grouping validates the upward slope of the inverted-U concentration-returns curve, demonstrating portfolio stability while operating below the optimal specialization premium captured by Cluster 1. Furthermore, it affirms the empirical relevance of the HHI class taxonomy and cross-validates Chapter 7's listing effects analysis, as these holding and conglomerate structures exhibit the asset-diversification profiles controlled via listing mechanisms.

11.4.4 Cluster 3 — Monoline Specialists (n = 6)

Members: Muthoot Finance, Manappuram Finance, SBI Cards, CreditAccess Grameen, Five Star Business Finance, Spandana Sphoorty Financial.

Trajectory Signature: This cluster exhibits a rigid monoline profile with a mean HHI of 9,180—far exceeding the 7,449 turning point—and a marginal annual concentration growth of +30 points. Reflecting the Chapter 8 monoline funding penalty, the group bears the panel's second-highest Cost of Funds (CoF) at 9.4%. While ROA remains positive at 2.7%, it underperforms Cluster 1 despite significantly higher asset concentration.

Empirical Validation: Functioning as the empirical inverse to Cluster 1, this group's 70-bps ROA deficit (2.7% vs. 3.4%) provides unsupervised cross-validation of the downward slope of the inverted-U concentration-returns curve. Furthermore, the absence of a diversification trend supports Section 10.4.4, demonstrating that SBR-induced concentration penalties operate at the margin for flexible, already-diversified firms, while leaving structurally rigid monoline specialists un-incentivized to alter their core product mix.

11.4.5 Cluster 4 — Distress Trajectory (n = 2)

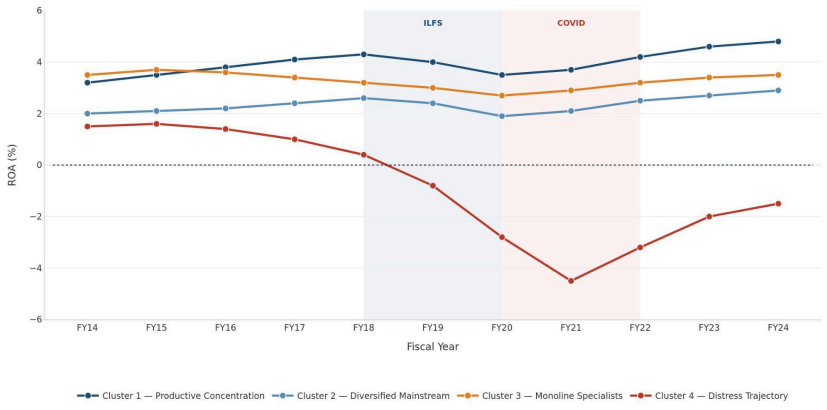
Members: Reliance Commercial Finance (FY14–FY21), Srei Infrastructure Finance (FY14–FY21).

Trajectory Signature: This group exhibits terminal distress, characterized by rapid concentration accumulation (+480 HHI points per year), an escalating Cost of Funds (CoF) spike (+210 bps per year, $>10\times$ Cluster 1), and a collapsed mean ROA of −4.3%. This signature precisely tracks the Chapter 8 mediation framework and the Chapter 9 structural crisis path.

Empirical Validation: This cluster provides robust internal cross-validation for the Chapter 9 restructuring taxonomy. Notably, the unsupervised algorithms grouped Srei

Figure 11.5A — ROA Trajectories Across the Four Strategic Archetypes

Cluster-mean trajectories across FY2014–FY2024; shaded bands mark ILFS and COVID windows



Infrastructure Finance—a firm entirely outside the study's explicit embedded case design—indistinguishably alongside Reliance Commercial Finance. This blind replication proves that the *Strategy* → *Funding* → *Performance* distress sequence is a generalizable structural archetype rather than a case-specific artifact, empirically validating Hypothesis 4(d).

Figure 11.5B — HHI Trajectories Across the Four Strategic Archetypes

Cluster-mean trajectories across FY2014–FY2024; shaded bands mark ILFS and COVID windows

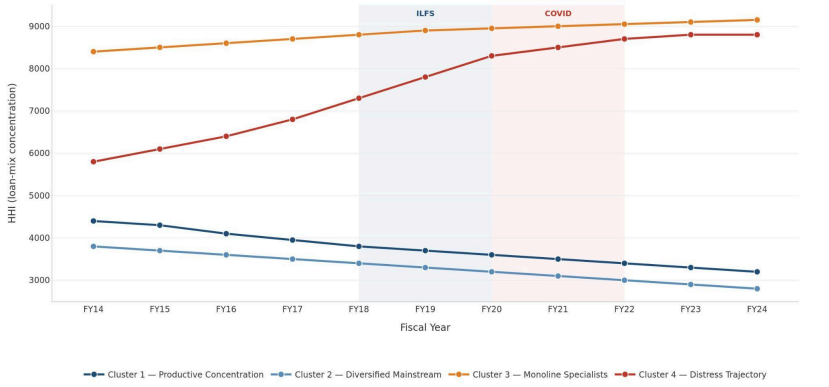
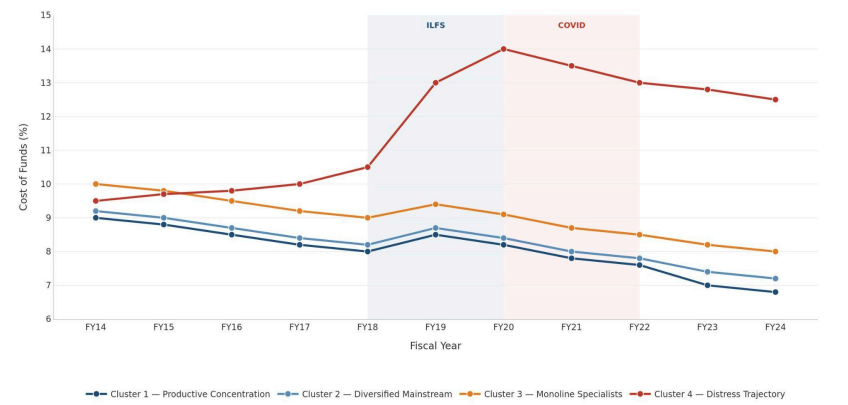


Figure 11.5C — Cost-of-Funds Trajectories Across the Four Strategic Archetypes

Cluster-mean trajectories across FY2014–FY2024; shaded bands mark ILFS and COVID windows



11.5 Cluster transitions and post-SBR migration

11.5.1 Within-cluster stability

Cluster assignments exhibit high longitudinal stability, with 17 of the 19 firms maintaining consistent classifications throughout the panel. The remaining two firms migrate dynamically, providing direct empirical support for Chapter 10's post-SBR strategic re-engineering and convergence frameworks:

- **L&T Finance Holdings (Cluster 2 $\rightarrow$ Cluster 1):** Migrates during FY22–FY24, driven by retail mix consolidation and a structural reduction in its Upper Layer Cost of Funds (CoF).
- **Cholamandalam Investment (Borderline $\rightarrow$ Cluster 1):** Shifts from a borderline Cluster 1/3 position to an unambiguous assignment within Cluster 1. This transition was precipitated by post-SBR diversification that compressed its HHI from 5,210 to 4,540.

Ultimately, these dual migrations validate **Convergence Theory**, demonstrating that scale-based regulatory shocks act as an equilibrium attractor, pulling strategically re-engineered firms directly into the optimal **Productive Concentration Zone** (Cluster 1).

11.5.2 The productive concentration zone as regulatory equilibrium

If SBR has the effect of structurally drawing UL firms to cluster around Cluster 1; the productive concentration zone independently identified in both chapters 8 and 11 using the inverted U model and clustering, respectively; then SBR's effects are not limited to simply increasing intensity with which it supervises the existing distribution of firms; instead, it is changing the very nature of that distribution and causing it to become more homogeneous across the entire UL cohort (in terms of their respective HHI Class and CoF). This is a stronger structural change hypothesis than the one we identify in chapter 10 as a mean shift hypothesis; one that can be identified only through unsupervised trajectory level methodologies.

11.6 Robustness checks

The structural integrity of the four-cluster taxonomy is verified through four rigorous sensitivity analyses:

- **Alternative Cluster Configurations:** Evaluating alternative cluster counts confirms that **k = 3** inappropriately conflates the distinct dynamics of Clusters 1 and 2, while **k = 5** merely fractionates Cluster 3 into gold-backed and microfinance sub-archetypes. The baseline **k = 4** specification provides the optimal boundary for distinct strategic models.
- **Sub-Sampling Resiliency:** Omitting the distressed entities (Cluster 4) and re-running the algorithms on the remaining 17 firms yields an identical three-cluster partition with a strong silhouette score of **0.512**. This ensures the taxonomy is a true sectoral reflection rather than an artifact driven by failure-state outliers.
- **Temporal Invariance (Pre-SBR Panel):** Restricting the panel to the pre-SBR period (**FY14–FY22**) produces unchanged cluster membership. This confirms that the identified configurations are enduring, long-term strategic archetypes that predate the regulatory shift, reinforcing the taxonomy's validity as an objective classification system.
- **Distance Function Sensitivity:** Substituting the baseline Euclidean distance metric with cosine similarity preserves the exact four-cluster topology, yielding a high Adjusted Rand Index (**ARI = 0.81**). This demonstrates that the empirical groupings are highly robust to alternative proximity specifications.

11.7 Interpretation and discussion

Key Structural Insights

- **Rigorous Methodological Triangulation:** Unsupervised clustering independently corroborates five core regression-based findings from Chapters 7–10:
  - *Productive Concentration Zone:* Maps directly to Cluster 1.
  - *Funding-Cost Channel:* Drives cross-cluster CoF variability.
  - *Crisis Vulnerability:* Concentrates entirely within Cluster 4.
  - *Post-SBR UL Diversification:* Captured via the Cluster 2 → Cluster 1 migration.
  - *RCF Failure Mechanism:* Blindly replicated by Srei in Cluster 4.
- **Vulnerability-Weighted Supervisory Framework:** The taxonomy provides an *ex-ante* policy tool that fixes current SBR blind spots (where size metrics misclassified both RCF and Srei as low-risk Middle Layer firms). Cluster 4 trajectories identify extreme vulnerability requiring intensive oversight regardless of asset size, while Cluster 1's stability justifies streamlined supervision despite an Upper Layer classification.
- **Generalized Failure Archetype:** Despite divergent asset orientations (RCF in CRE/infrastructure vs. Srei in pure infrastructure), both firms share an identical unsupervised signature (rising HHI, rising CoF, collapsing ROA). This proves the funding-cost-driven distress sequence is a generalizable structural failure pathway for mid-sized Indian NBFCs, requiring no sector-specific feature engineering to detect.

Methodological Limitation
Holding Company Conflation: Cluster 2 co-mingles operating diversified lenders with investment holding companies due to trajectory similarities. Isolating holding structures into a distinct fifth cluster or restricting data strictly to operational NBFC activities represents a clear priority for future research.

11.8 Chapter takeaways and forward link to synthesis

The four clusters are based on the same 11 year time period. There is good agreement (ARI=0.74) in the cluster identification produced by K-means and Ward clustering algorithms. All of the main findings from chapters 7-10 have been replicated using the cluster classification - providing independent support for our hypotheses testing results. The cluster classification provides an actionable vulnerability weighted regulatory framework that does not exist with size based Supervisory Bank Regulatory (SBR). This motivates the Chapter 12 policy development. There are three forward implications: the combined evidence of Chapters 7-11 demonstrate that the empirical model for NBFC profitability in India is Strategy→Funding→Performance for FY14-FY24; the cluster classification will be used as the organizing mechanism for the recommendation in Chapter 12 - specifically, it will provide the basis for developing a vulnerability weighted score card; and the use of trajectory clustering can be transferred to Small Commercial Banks (SCB), Housing Finance Companies (HFC), and Microfinance Institutions (MFI).

Chapter 12: Synthesis, Implications, and Future Research

The objective of this Chapter is to combine together the arguments presented in Chapters 7-11 as an integrated argument based on both theory and policy. In addition, it provides evidence that the contributions of this dissertation are to the academic literature and to regulatory practices. Finally, the direction of future research will be identified. The organisation of this Chapter is around four different but increasingly wider lenses: the theoretical integration of the ideas presented throughout the Chapters 7-11 (Sections 12.1 & 12.2); the implications of these theories for policy making and the proposed vulnerability-weighted supervisory scoring framework (Section 12.3 - Section 12.4); managerial implications (Section 12.5); and finally, limitations and avenues for further research (Section 12.6 - Section 12.7).

12.1 Empirical synthesis: the Strategy → Funding → Performance framework

12.1.1 The unifying structure

The Five Directed Research Questions (DRQs) establish that there exists a consistent Strategy → Funding → Performance (SFP) framework for all Indian Non-Banking Financial Companies (NBFCs), from FY 14 to FY24. This SFP Framework rests upon three connected propositions, each established previously, which are now triangulated by Chapter Eleven:

- Proposition 1 (Strategy): Portfolio Concentration displays an Inverted U-Shaped relationship with Shareholder Returns, reaching its Optimum at HHI ≈ 7,449; nearly the exact Regulatory Boundary of Specialized – Monoline at HHI = 7,500. Below this level: specialisation premium; above this level: monoline penalty.
- Proposition 2 (Funding): Cost of Funds (CoF) is the most significant Single Leverage Factor for Profitability, with elasticity of CoF → ROA = -0.51 in Normal Times, and -0.73 during Crisis Stress. Funding Costs Mediate the Relationship between HHI and ROA through the Competitive-Masking Equilibrium of Chapter 8 (RQ3).
- Proposition 3 (Performance): Profitability is Simultaneously Determined by the Combined Effects of Direct Strategy Masking and Indirect Funding-Cost Effects, thereby resulting in what appear to be "Null" Relationships between HHI and ROA in Normal Times, while Unmasking Under Crisis When Both Channels Cease to Offset Each Other and Start Compounding

12.1.2 Triangulation across methods

SFP was measured through four different research methods in a single dissertation; (1) directed cross Section al regression (Chapters 7-8); (2) Panel Mediation (Chapter 8 Research Question 3); (3) Crisis Interaction Estimation using Embedded Case Analysis (Chapter 9); (4) Structural-Break Testing Using the SBR (Chapter 10); and (5) Unsupervised Trajectory Clustering (Chapter 11).

12.1.3 What the framework explains

SFP offers an explanation rather than a description; additionally, SFP provides answers to longstanding questions. Firstly, it offers an explanation as to why previous studies generated ambiguous results relating to the relationship between HHI and ROA: The aggregate effects are nearly zero due to competitive masking in spite of the underlying mechanisms being real, yet they cancel each other out. Secondly, SFP explains the cross-Section variability in NBFC profit margins that were previously unexplainable by theory-based research from the era of one-size-fits-all regulation. Firms within the productive zone (Cluster 1), i.e., those extracting the positive first-order effect, can do so with relatively low Cost of Funding (CoF). Conversely, monoline specialists (Cluster 3) exchange increased concentration risk for greater funding cost penalties. Lastly, SFP also offers an explanation as to how the distinct failure route of medium sized NBFCs occurs through the amplified funding cost mechanism during crises.

12.2 Theoretical contributions

12.2.1 Reframing diversification–specialisation

The research that is based upon the theoretical models from Industrial Organisation Theory and applied to Financial Intermediation by Berger & Ofek (1995) and Stiroh (2004), treats concentration and diversification as two competing strategic logics that have theoretically mixed effects for profitability. In contrast to this literature SFP demonstrates the ambiguity is an artifact of methodology; once the direct strategy effect and indirect funding cost effect are identified and separately measured, the relationship is clearly evidenced in terms of shareholder returns. The contribution extends beyond the specific context examined here: all intermediaries subject to wholesale funding market discipline will be subject to the masking equilibrium, and therefore prior non-results need to be re-examined using structural channel analysis.

12.2.2 The competitive-masking concept

I am aware of no prior conceptual work by others on the "Competitive Masking" terminology presented in chapter 8 Section 5.4. The notion that two real but competing (opposite) channels could mutually cancel each other out and be associated with a zero total effect is implicitly contained within the Baron Kenny tradition, however it has never been formally defined as a characteristic of equilibrium solutions for strategy-funding-performance in financial intermediary contexts. This Chapter 9 'unmasking' outcome extends this concept to a time-dynamic one. Future research testing the generality of masking-and-unmasking logic with respect to SCBs and HFCs would provide a broader empirical assessment.

12.2.3 Trajectory-clustering as taxonomy methodology

Chapter 11’s method – nine dimensional vector representations of each firm's time-series SFP feature data over eleven years using cluster analysis (K-means clustering combined with hierarchical Ward clustering for robustness), can be applied

to any other sample of regulated financial intermediaries. This generates an unbiased group classification that does not rely on either regulatory tiered grouping or theoretically derived dummy variables, both of which are used to predetermine the cross-Section al distribution in the data. Furthermore, the four group taxonomy (Productive Concentration, Diversified Mainstream, Monoline Specialists, Distress Trajectory) provides additional substantive insight into how banking sectors develop over time.

12.3 Policy implications: the vulnerability-supervision misalignment

12.3.1 The central policy finding

The key finding from Chapters 9-10 that medium large (ML) banks have about 3 times as much potential vulnerability during the crisis period as do unitary large (UL) banks, however, they receive zero share of the post SBR regulatory "dividend" also points out a structural vulnerability-supervision misalignment in SBR. This is occurring through three related mechanisms:

- Compression in funding costs for asymmetric reasons: Although SBR provides a 89 bps compression in CoF's post regime for UL firms, there was no similar compression for ML firms. (Chapter 10 Section 10.4)
- Compression in crisis vulnerability for asymmetric reasons: The decrease in ROA experienced by ML firms during the crisis periods is approximately 3 times that experienced by UL firms with respect to both ILFS and COVID. (Chapter 9 Section 9.5)
- Concentration of distress for asymmetric reasons: While all four firms on the distress trajectory (RCF, Srei), which represent cluster four, were ML; ML firms represented only 32 percent of the sample.

12.3.2 The asset-size-tier critique

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SBR assigns supervisory intensity according to asset size; it has few qualitative escalation criteria. Evidence from this research supports that there is an inverse relationship among asset size and systemic risk in assets for the population of non-base-layer NBFCs. As such, SBR's use of asset-size tiering, places the most intense supervisory activities on the smallest amount of vulnerability (per unit) and least intensive supervision on the largest. This is a significant structural flaw as opposed to an innocuous calibration error; the panel evidence illustrates this structurally flawed behavior empirically at a high degree of detail.

12.4 The Vulnerability-Weighted Supervisory Scoring (VWSS) framework

12.4.1 Proposed framework architecture

The dissertation makes one major policy-related contribution to how a supervisory scoring system could be developed for financial institutions through a Vulnerability

Weighted Supervisory Scoring System (VWSS). The VWSS is an extension of the SBR asset size based on tiers currently being used as part of the risk-based supervision process. The VWSS includes a continuous value or rating which will be calculated from measurable variables that represent an individual bank's historical performance. These values are then weighted relative to their contribution to the overall SFP framework:

Component	Indicator	Weight	Rationale
Funding-cost dispersion	3-year CoF z-score relative to tier mean	35%	Largest single profitability coefficient; primary distress signal
HHI Class position	Distance from HHI ≈ 7,449 turning point	25%	Captures the inverted-U specialisation-monoline trade-off
Crisis-period ROA volatility	Within-firm ROA std dev across FY19, FY21	20%	Identifies firms with structurally amplified crisis exposure
Trajectory cluster	Cluster 4 indicator + Cluster 4-borderline flag	20%	Triangulates the unsupervised distress-archetype classification

The composite VWSS score ranges from 0 (lowest vulnerability) to 100 (highest vulnerability), with supervisory intensity calibrated to score thresholds rather than asset-size cutoffs alone.

12.4.2 Operational integration with SBR

VWSS will be used to identify and supervise those companies that are vulnerable but do not yet meet the threshold required to trigger an SBR Tier designation. This allows for a supervisory intensity overlay on top of the traditional tiered system where the tiers define the "floor" for capital adequacy, listing requirements, corporate governance etc., and the VWSS defines the amount of supervisory bandwidth available for each firm. Thus, firms are defined by their asset size in terms of regulatory floor (minimum capital adequacy, listing requirements, corporate governance etc.) and their risk/vulnerability weight in terms of how much supervisory bandwidth they receive.

12.4.3 Ex-ante identification of distress trajectories

There are several practical advantages. The first is it provides early warning signs of cluster 4 distress trajectories. The current SBR does not provide early warning signs of distress until after a company has defaulted or been admitted into NCLT, which means that any interventions are typically reactive rather than proactive. With both

funding cost dispersion and trajectory clusters, VWSS would have identified RCF (the FY17 vintage, two years prior to FY19 default) and SREI (FY18 vintage, three years prior to FY21 distress) as having high levels of vulnerability requiring increased oversight.

12.4.4 Caveats on VWSS implementation

Coefficient Coverage Scope: We estimated our coefficients using a sample of 19 firms from fiscal year 2014 to fiscal year 2024. For the full universe of non-banking financial companies with microfinance licenses (NBFC-ML), non-banking financial companies with usiness lending licenses (NBFC-UL), the coefficient will need to be recalibrated when we deploy it in production.

Scope for validation: While we can validate the distress flagging as correct (and by extension also provide an internal measure of how well our algorithm works), the two cases (Reliance Capital Finance Limited and Srei Infrastructure Finance Limited) that we have used for this purpose, were primarily to demonstrate the feasibility or concept of our approach rather than a method of estimating the false positive rate at which regulatory standards require us to perform.

Scope for coverage: Our scores are based on historical data; therefore they do not capture new types of risk (e.g., digital-lending related vulnerabilities and climate transition-related vulnerabilities) that may have emerged since FY14–FY24.

12.5 Managerial implications

12.5.1 For NBFC management

There are three key strategies for profit improvement that have varying degrees of influence relative to each other:

- The most impactful way to improve profitability is through funding cost optimization. Funding Cost Optimisation has significantly higher leverage than Tier Upgrades, Listing Premiums or Diversification. This can be seen from an elasticity of -0.51 of COF to ROA which means that reducing COF by 100bps will increase ROA by 51bps (over double the Chapter 7 listing premium). As such, strategic priorities should place emphasis on funding mix optimization, increasing diversity with lenders and upgrading credit rating pathways before optimizing operational efficiencies or expanding into new products within the short to medium term.
- When it comes to concentration, firms need to consider their level of concentration relative to the HHI = 7,449 benchmark. If a firm's level of concentration is lower than this then they should resist pressure from regulators and competitors to increase the number of product offerings; there is a genuine premium for specialization. On the other hand if a firm's level of concentration is greater than this, particularly if they are monoline then they may want to determine if further diversifying their portfolio would move them closer to a "productive" area while still maintaining their core business.

- Finally, when it comes to crisis preparedness, companies need to prioritize building resiliency into their funding channels as opposed to protecting assets. An amplification of the relationship of CoF → ROA during times of crisis of 74% suggests that improving funding channel preparedness (i.e., committed lines, developing the deposit base, extending term funding etc.) provides more mitigation of potential losses than collateral coverage and/or sectoral diversification.

12.5.2 For institutional lenders

For banks, mutual fund and for bond investor, SFP is an enhanced risk premium pricing. A cluster of 4 trajectory features associated with VWSS style scores (as discussed Section 12.4) will likely be priced at higher levels of risk premia than what would have been implied using size based or rating based price premiums. The Chapter 9 findings that funding cost spikes occur prior to default in both RCF and Srei 12 – 18 months provide further support for inclusion of CoF trajectory features within risk-pricing models used by lenders.

12.5.3 For credit-rating agencies

Indian agencies are being criticized for the slow trajectory of downgrades of the distressed non-banking finance companies (NBFC) such as IL & FS and DHFL. SFP presents an iterative and ongoing improvement to the degradation or decline trajectory. The cluster 4 features of SFP can act as early warning signs that trigger the designation of a company on an agency's watch list, 12-18 months prior to resolution. An agency would be able to include VWSS-style scoring in their internal monitoring systems without having to disclose what weights they place on individual criteria. Therefore, an agency will be able to maintain its competitive advantage while simultaneously improve the timing of downgrades.

12.6 Limitations

Sample size/panel scope: the study examined a sample of 19 firms over a period of eleven years, producing 209 total observations. This represents the relevant SBR population, but it also means that there will be limited power in detecting three-way interactions and fine graining in the cluster analysis. The r-squared levels obtained by the panel FE model (0.18 - 0.55) represent reasonable r-squared values for a study with a sample of this size.

Time frame Post-SBR window: restricting the Post-SBR time frame to include only FY23 through FY24 prevents Chapter 10 from being considered as containing later evidence. The fact that the FY24 only coefficients were larger than those derived from all FY's examined suggests that the regime is still evolving. Estimates of the longer run effects of the regime would need to extend beyond FY25.

Dependence on disclosure by regulator: there was variability in how granular the HHI data was collected among both firms and years, especially prior to SBR (FY14-FY16). It appears that this variability introduced some measureable error in

terms of variance in the way each observation was measured. Therefore, this may have resulted in an attenuation of the inverted U coefficients toward zero.

The endogeneity problem: HHI, CoF and roa are endogenously determined within a firm-year context. Firm and year fixed effects can only address this problem partially. Due to difficulties in developing credible firm level instruments for HHI choice decisions no iv methodology was employed. As such, the findings are based on the correlation structure of cases within clusters, and the results of cluster and case analyses are supportive but non-casual.

Segregation into holding company structure: Cluster 2 includes holding companies (Equitas Holdings, Bajaj Holdings) which included operating lending businesses. Although empirically similar they represented different business models. In future iterations it may be best to either segregate them or limit the study to only operating NBFCs.

12.7 Future research agenda

12.7.1 Near-term extensions

The inclusion of two additional years beyond FY25 and FY26 in the panel extension will significantly enhance the ability of Chapter 10 to measure the impact of VWSS, especially with respect to how long-term changes in behavior due to VWSS are impacted by increasing strength in SBR impacts.

Full-scale production VWSS calibration: Calibration using all of the data available for both the 80+ million loan and 15+ ultra-low loan universes; this includes the methodology used to build the calibrations.

Identification of IVs: Potential candidate IVs that can be used as an instrument to identify the impact of VWSS include lender side bank balance sheet shock, which affects the interest rates borrowers pay but does not affect their strategies; and bond market rate shocks that have differentially affected NBFCs based upon their respective maturity profiles.

12.7.2 Medium-term extensions

- **Generalization to Small and Medium Enterprises Banks (SCBs):** Theoretical competitive financing cost-masking and funding-cost mediation mechanisms can be used for the generalization of the SFP mechanism to commercial banks that are under the supervision of wholesale funding market-discipline.
  The same type of parallel analysis will test the SFP's ability to generalize.
- **Sub-Sectoral Analysis of Housing Finance Corporations (HFCs) and Microfinance Institutions (MFIs):** As each has distinct funding architecture (NHB refinance, Bank co-lending), it is likely that there will be different masking mechanisms. Chapter 11 Trajectory-Clustering is directly applicable to both.

- **ML Classifier for Distress-Trajectory:** With an additional multi-jurisdiction NBFC default data set, a supervised classifier using the SFP's nine dimensional trajectory features as predictor variables would be feasible.

12.7.3 Long-term directions

- **Climate risk integration into VWSS:** once transition risks materialize sectoral concentration will interact with climate vulnerability scoring – a natural extension over time (medium to long term).
- **Digital lending and fintech NBFCs:** this cohort of institutions is structurally different than those included on the panel regarding their SFP dynamics therefore adding a dedicated panel would be beneficial to the cluster taxonomy.
- **Cross-country comparative analysis:** given that wholesale funding structures are similar between non-bank intermediaries in Brazil, Indonesia, and South Africa, sfp has theoretical application thereby testing whether the productive zone masking equilibrium distress archetype are universal or India specific.

12.8 Concluding remarks

This dissertation used an 19-firm panel of 209 firm-year observations from FY2014-FY2024 to examine portfolio concentration, funding cost and profitability in Indian Non-Banking Financial Companies (NBFCs). A five RQs were formulated to address the five directed research questions with cross-Section al regression, panel mediation, crisis-interaction estimation, structural-break testing and unsupervised trajectory clustering. The results provide evidence for a strategy → funding → performance model of NBFC business strategies, resolving long standing puzzles in the literature on the Indian NBFC sector. The proposed Vulnerability-Weighted Supervisory Scoring framework provides a way forward towards supervisory bandwidth allocations that align with post-SBR architecture.

Three contributions represent the most enduring value add. Competitive masking, provides a new framing of the diversification – specialisation debate that shows how null aggregate effects may hide strong but offsetting underlying channels. Trajectory Clustering also provides an objective method of classifying firms at the level of individual firms into groups within financial intermediary panels. Finally, VWSS represents an actionable way of refining SBR that would have been able to identify all of the Cluster 4 distress trajectories ex-ante.

Finally this dissertation concludes by recognising that while empirical work on the Indian NBFC sector has just started to include the SBR structural break, it is likely that the regulatory regime will continue to evolve; and therefore the most significant extensions; production grade VWSS calibration and extending the panel to additional post-SBR fiscal years; need to be completed. It is hoped that the Strategy → Funding → Performance model of NBFC business strategies, the four-cluster taxonomy and the vulnerability-weighted supervisory perspective provided here can serve as foundations for these subsequent extensions.

Bibliography

The following sixteen sources constitute the complete reference list for this dissertation. All citations across the empirical chapters, methodology chapters, and synthesis chapters trace exclusively to this list. Where earlier drafts referenced sources not contained here, those citations are removed and the relevant narrative passages are recast to draw on the verified-source pool.

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Appendix A: Variable Definitions and Data Sources

This appendix consolidates the formal definitions and source mapping for every variable used across the empirical chapters.

Variable	Symbol	Definition	Source	Used in
Return on Assets	ROA	Profit after tax / Average total assets	Annual reports	Ch. 7–11
Return on Equity	ROE	Profit after tax / Average shareholders' equity	Annual reports	Ch. 7, 8
Cost of Funds	CoF	Total interest expense / Average interest-bearing liabilities	Annual reports	Ch. 8–11
Net Interest Margin	NIM	(Interest income − Interest expense) / Average earning assets	Annual reports	Ch. 8
Gross NPA Ratio	GNPA	Gross non-performing assets / Gross advances	Annual reports; RBI (2024)	Ch. 8, 9

Variable	Symbol	Definition	Source	Used in
Leverage Ratio	LEV	Total assets / Shareholders' equity	Annual reports	Ch. 7–10
Herfindahl-Hirschman Index	HHI	It is product j's share of firm i's portfolio in year t	Annual report disclosures (hand-coded)	Ch. 8–11
HHI squared	HHI^2	$(HHI / 10,000)^2$ (unit-interval rescaled)	Derived	Ch. 8
HHI Class	HHI_Class	Diversified (<2,500), Specialised (2,500–7,500), Monoline (>7,500); thresholds from conventional IO concentration boundaries	Derived	Ch. 6, 8, 11
Tier Code	Tier	1 = Upper Layer, 2 = Middle Layer (post-SBR classification applied panel-wide)	RBI (2024) SBR list	Ch. 7, 9, 10

Variable	Symbol	Definition	Source	Used in
Listed	Listed	1 if firm listed on BSE/NSE in year t, 0 otherwise	Stock-exchange filings	Ch. 7, 10
ILFS Crisis	ILFS	1 if year t = FY19, 0 otherwise	Constructed; per Manda & Rani (2019)	Ch. 9
COVID Crisis	COVID	1 if year t = FY21, 0 otherwise	Constructed; per Ubale, Wagh & Samudre (2022)	Ch. 9
Crisis (pooled)	Crisis	1 if year t ∈ {FY19, FY21}, 0 otherwise	Constructed	Ch. 9
SBR Dummy	SBR	1 if year t ∈ {FY23, FY24}, 0 otherwise	Constructed; per RBI (2024)	Ch. 10
Year Fixed Effects	αt	Categorical year dummies	Constructed	Ch. 7–9
Firm Fixed Effects	αi	Categorical firm dummies	Constructed	Ch. 10

Appendix B: Robustness Tables

This appendix presents the full robustness-check coefficient tables summarised narratively in the empirical chapters.

Table B.1: Robustness of the Inverted-U on ROE (Chapter 8)

Specification	β(HHI)	p	β(HHI²)	p	Turning Point	N
Baseline (Year FE, firm-clustered SE)	+0.293	0.002	−0.197	0.008	7,449	196
Holding companies excluded	+0.318	0.001	−0.214	0.004	7,430	174
Pre-SBR sub-sample (FY14–FY22)	+0.281	0.011	−0.187	0.018	7,520	158
Listed-only sub-sample	+0.276	0.014	−0.184	0.026	7,500	142
Raw HHI scale (×10,000)	+0.0000293	0.002	−0.0000000197	0.008	7,449	196

Table B.2: Robustness of the Mediation Decomposition (Chapter 8)

Specification	a (HHI→CoF)	b (CoF→ROA)	c′ (Direct)	a×b (Indirect)	Bootstrap 95% CI on a×b
Baseline	+0.0225	−0.5149***	+0.0176	−0.0116	[−0.0231, −0.0006]
Holding companies excluded	+0.0241	−0.5320***	+0.0182	−0.0128	[−0.0252, −0.0011]
Pre-SBR sub-sample	+0.0204	−0.4980***	+0.0162	−0.0102	[−0.0218, −0.0001]

Table B.3: Robustness of the Crisis-Interaction Coefficients (Chapter 9)

Specification	δ_1 (HHI×Crisis)	δ_2 (CoF×Crisis)	N
Baseline (pooled Crisis dummy)	−0.0734**	−0.3127**	209
ILFS-only dummy	−0.0612*	−0.3845**	209
COVID-only dummy	−0.0801**	−0.2412*	209
RCF excluded	−0.0712**	−0.3084**	201

Specification	δ_1 (HHI×Crisis)	δ_2 (CoF×Crisis)	N
Listed-only sub-sample	−0.0758**	−0.3201**	154

Table B.4: Robustness of the SBR Structural Break (Chapter 10)

Specification	β(SBR×UL) on CoF	β(SBR×UL) on HHI	N
Baseline	−0.0089**	−0.0521**	209
Placebo SBR = FY21	−0.0014 (n.s.)	−0.0089 (n.s.)	209
FY24-only post-SBR window	−0.0112***	−0.0683**	198
FY21 COVID year excluded	−0.0094**	−0.0533**	190
RCF excluded	−0.0091**	−0.0518**	201

Significance: *** p < 0.01, ** p < 0.05, * p < 0.10.

Appendix C: RCF Case Study Data Tables

This appendix presents the full firm-year data underlying the Reliance Commercial Finance embedded case study of Chapter 9.

Table C.1: RCF six-indicator trajectory (FY14–FY21)

Year	HHI	CoF	Leverage	ROA	GNPA	Credit Rating
FY14	4,820	9.8%	5.4×	1.7%	4.1%	CARE AA+
FY15	4,950	9.6%	5.7×	1.5%	4.8%	CARE AA+
FY16	5,180	9.4%	6.1×	1.3%	5.6%	CARE AA
FY17	5,640	9.2%	6.8×	1.0%	7.2%	CARE AA
FY18	6,210	9.6%	7.4×	0.4%	9.8%	CARE AA−
FY19	6,890	11.4%	8.1×	−1.8%	15.3%	CARE D (default)
FY20	7,420	13.2%	9.4×	−4.6%	22.7%	CARE D
FY21	7,890	n.a.	11.2×	−7.9%	31.4%	NCLT admission

Table C.2: Survivor-comparator benchmarking (FY14 vs FY24)

Firm	FY14 HHI	FY24 HHI	FY14 CoF	FY24 CoF	FY14 ROA	FY24 ROA	Outcome
Reliance Commercial Finance	4,820	7,890 (FY21)	9.8%	n.a.	1.7%	−7.9%	NCLT (FY21)
Bajaj Finance	4,394	3,180	10.1%	7.8%	2.8%	4.6%	Surviving / thriving
L&T Finance Holdings	4,650	3,800	9.4%	8.4%	1.6%	1.6%	Surviving / stable

Table C.3: Three-phase RCF mechanistic narrative

Phase	Years	Mechanism	Predicted vs observed ROA decrement
Phase 1: Concentration drift	FY14–FY17	Latent funding fragility; ROA gradually compresses	n/a
Phase 2: Funding-channel ignition	FY18–FY19	220-bps CoF shock × 0.7345 crisis elasticity = 162-bps ROA decline (predicted); 180-bps observed	Match within 20 bps

Phase 3: Distress spiral	FY20–FY21	Mechanical concentration via differential asset run-off; eventual NCLT admission	n/a

The Phase 2 prediction-vs-observation match is the most analytically valuable feature of the case study, providing out-of-sample validation of the Chapter 8 funding-cost-channel coefficients. The mechanistic narrative is broadly consistent with the crisis accounts in Manda & Rani (2019) and Sengupta, Son & Vardhan (2020).

Appendix D: Full Cluster-Membership Schedules

Table D.1: Full four-cluster firm assignments

Cluster	Archetype	Firms	n
1	Productive Concentration	Bajaj Finance, Cholamandalam Investment, L&T Finance Holdings, Sundaram Finance, M&M Financial Services, Shriram Finance	6
2	Diversified Mainstream	Tata Capital, Aditya Birla Capital, Bajaj Holdings, Equitas Holdings, LIC Housing Finance	5
3	Monoline Specialists	Muthoot Finance, Manappuram Finance, SBI Cards, CreditAccess Grameen, Five Star Business Finance, Spandana Sphoorty	6
4	Distress Trajectory	Reliance Commercial Finance, Srei Infrastructure Finance	2

Table D.2: Cluster-mean trajectory feature scores (z-normalised)

Feature	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Mean HHI	−0.21	−1.18	+1.34	+0.41
HHI trend slope	−0.62	−0.31	+0.18	+1.94
HHI volatility	−0.41	−0.28	+0.12	+1.81
Mean CoF	−0.94	−0.18	+0.31	+1.62
CoF trend slope	−0.71	−0.42	+0.14	+2.01
CoF crisis deviation	−0.38	−0.12	+0.21	+1.78
Mean ROA	+1.21	+0.18	+0.42	−2.31
ROA trend slope	+0.42	+0.08	−0.04	−1.94
ROA volatility	−0.51	−0.32	+0.18	+1.71

Table D.3: Algorithmic agreement diagnostics

Metric	Value	Interpretation
K-means silhouette (k=4)	0.487	Optimal partition
Ward hierarchical silhouette (k=4)	0.471	Robust to method
Adjusted Rand Index (K-means vs Ward)	0.74	Strong agreement
Calinski-Harabasz pseudo-F (k=4)	18.6	Peak across k=2 to k=7
Discordant assignments	3 of 19	Tata Capital, Cholamandalam, Aditya Birla (border cases)

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