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Securitization X-Ray: Direction of Collections as a Leading Signal of Stress in Indian Securitised Pools (2023–2026)

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Abstract

Investors who buy pass-through certificates backed by Indian retail loans judge pool health mainly by the level of monthly collections. This study asks whether the direction of collections—the change in the three-month average collection ratio from one quarter to the next—holds information that the level misses, and whether it warns of stress sooner. Monthly median collection ratios for six asset classes (vehicle, microfinance, mortgage, small business, personal and two-wheeler loans) were transcribed from eight CRISIL Ratings pool-performance reports published between May 2024 and September 2026. Overlapping reports allowed an internal accuracy check: 356 of 359 transcribed values agreed exactly. The resulting panel holds 182 asset-class-months from April 2023 to June 2026. One-way ANOVA, fixed-effects panel regressions with a placebo variable, the signals approach to early warning and an out-of-sample forecast test were applied. Collection performance differed sharply by asset class ($F = 18.44$, $p < 0.001$). After controlling for the current level, a one-point decline in direction was followed by a next-quarter collection ratio about 0.35 points lower ($t = 4.89$), raising explained variance from 0.802 to 0.834 and cutting out-of-sample forecast error by 7.2 per cent. Raw month-on-month changes carried no information. Direction turned negative in February 2024, four months before microfinance collections fell below 95 per cent, while the level still read 97 per cent; reading level and direction together reduced the false-alarm rate from 19.8 to 4.7 per cent. Credit enhancement absorbed the shock, as no microfinance pool drew on its cash collateral. The findings suggest that a simple two-lens monitor built from free public data can help investors, originators and supervisors see deterioration earlier.

Keywords: *Securitisation; Collection Efficiency; Early-Warning Signals; Microfinance; Panel Data.*

INTRODUCTION

India now securitises more retail credit than at any point in its history. Volumes touched ₹2.55 lakh crore in FY2026, with over 190 lenders selling pools of loans to investors (CRISIL Ratings, 2026b). For non-bank lenders such as vehicle financiers, microfinance institutions and housing finance companies, pass-through certificates (PTCs) are no longer an occasional source of money; they are a routine part of funding. The investor in a PTC, however, is repaid only from what borrowers in that specific pool pay each month. The monthly collection ratio (MCR)—the amount collected in a month as a share of the amount due—is therefore the single most watched indicator of a pool's health.

A large and growing market can still contain a segment in trouble. During FY2025, when total securitisation rose 24 per cent to a then-record ₹2.35 lakh crore (CRISIL Ratings, 2025b), the typical microfinance pool rated by CRISIL saw its median MCR slip from 98 per cent in December 2023 to 86 per cent a year later, reaching 83 per cent by February 2025 (CRISIL Ratings, 2025a, 2025d). Anyone watching only the level of collections would have noticed the problem once it had crossed a warning line—by which point it was already well under way.

This paper examines a practical proposition: the **direction** in which collections are moving tells an investor something that the **level** does not, and tells them earlier. The proposition draws on Demyanyk and Van Hemert (2011), who showed that the quality of U.S. subprime loans had been worsening for six straight years before 2007 and that the decline was visible in performance data well before the crisis broke. It also borrows the evaluation logic of the early-warning literature, in which an indicator earns its place only if it fires before trouble more often than it fires without reason (Kaminsky et al., 1998). Bringing these together, the study proposes and tests a transparent monitor called the **Securitization**

X-Ray, which reads every asset class through two lenses: how much is being collected, and which way that figure is heading.

The paper contributes in three ways. It builds, and checks for accuracy, a new monthly panel of asset-class collection ratios from publicly available CRISIL reports. It shows that a smoothed measure of direction adds significant forward-looking information over and above the level, both within the sample and on months the model has not seen, while raw monthly changes add nothing. And it documents that the structural protection built into Indian pools absorbed the largest collection shock of recent years, which speaks to the ongoing debate about how much credit enhancement a pool needs.

REVIEW OF LITERATURE

Why Pools Are Built the Way They Are

Theory explains why lenders pool loans, slice the pool into claims of different seniority and place it in a separate legal vehicle. DeMarzo and Duffie (1999) show that an issuer with better information than investors can still raise funds efficiently by selling a carefully designed claim and keeping part of the risk; DeMarzo (2005) adds that pooling dilutes this private information before tranching creates a safe senior claim. Gorton and Souleles (2005) describe the special purpose vehicle that keeps the pool insulated from the originator's own fortunes. These ideas account for the way Indian non-bank lenders structure PTCs, with a cash deposit, a junior tranche and surplus interest standing between borrower shortfalls and investors.

How Pool Quality Can Slip Unnoticed

The crisis literature is a reminder that the quality of securitised loans can erode without much outward sign. Loans that were easier to sell were screened less carefully (Keys et al., 2010); lenders that relied heavily on selling loans experienced worse performance once markets turned (Purnanandam, 2011); and lenders monitored securitised loans less closely (Wang & Xia, 2014). Rapid credit growth often came before defaults (Mian & Sufi, 2009; Dell'Ariccia et al., 2012). Structured products magnify small mistakes in assumed default rates (Coval et al., 2009), and credit ratings can trail the underlying collateral (Benmelech & Dlugosz, 2009; Griffin & Tang, 2012). Securitisation also brings genuine liquidity and funding benefits (Loutskina, 2011; Nadauld & Weisbach, 2012), and securitised corporate loans have not always underperformed (Benmelech et al., 2012). Taken together, this work argues for independent, transparent monitoring of how pools actually perform.

How Early Warnings Are Judged

Kaminsky et al. (1998) proposed judging a leading indicator by three numbers: how often it fired before a real crisis, how often it fired when nothing followed, and the ratio of the two, known as the noise-to-signal ratio. Kaminsky and Reinhart (1999) found that banking stress tends to build gradually rather than arrive suddenly. Borio and Lowe (2002) reported that sustained, cumulative deviations predict trouble better than one-period jumps, and Drehmann and Juselius (2014) argued that indicators used in policy must be timely, stable and easy to interpret. Similar lessons come from corporate distress prediction, where recent trends add power beyond levels (Shumway, 2001; Campbell et al., 2008), and from quality control, where moving averages filter noise before a shift is declared (Page, 1954; Roberts, 1959).

Indian Evidence and the Research Gap

Indian work has mostly looked at securitisation from the originator's side—for instance, how securitisation affected the liquidity and profitability of five financial institutions (Kiranmayi et al., 2025)—or at market structure and regulation (Romero-Torres et al., 2017; Reserve Bank of India, 2019, 2021). Research on microfinance documents the real economic cost of earlier collection crises (Mader, 2013; Breza & Kinnan, 2021). The author is not aware of any study that turns CRISIL's published pool-performance series into a verified panel, or that compares level-based and direction-based signals for Indian securitised asset classes. This paper addresses that gap.

METHODOLOGY

Research Problem, Objectives and Hypotheses

Problem. Pool monitoring in India relies mainly on the level of collections, which signals trouble late. Whether the direction of collections offers additional and earlier information has not been tested. **Objectives.** The study aims (i) to compare collection performance across six securitised asset classes, (ii) to test whether direction predicts future collections after allowing for the current level, (iii) to assess whether direction flags stress before the level crosses a warning threshold, and (iv) to examine whether credit enhancement absorbed the 2024–25 microfinance shock. **Hypotheses.** H1: mean collection ratios differ across asset classes. H2: given the current level, the quarterly direction of collections predicts next-quarter collections. H3: direction-based signals identify stress before the level breaches the threshold, with a noise-to-signal ratio below one.

Data and Verification

CRISIL Ratings, the largest rating agency for Indian securitisation, publishes pool-performance reports several times a year. Each report charts the monthly median MCR of

every major asset class and prints the value for each month. The author transcribed 359 such values from eight reports issued between May 2024 and September 2026 (Table 1), which is the most recent report available at the time of writing. Because consecutive reports cover overlapping months, the same month frequently appears in two, three or four reports. This overlap served as a built-in accuracy test: 356 of the 359 values (99.2 per cent) were identical to the value finally used. The three exceptions were one-point differences between an earlier and a later report and were settled by majority, with ties going to the later report. One series whose month labels appeared shifted by a month relative to three other reports was set aside. The final unbalanced panel covers six asset classes for between 18 and 38 months each, giving 182 asset-class-months from April 2023 to June 2026. Annual market volumes for FY2019–FY2026 come from CRISIL press releases and were cross-checked against ICRA Ltd. (2026).

Table 1. Pool-performance reports used

Source	Payouts covered	Asset-class series used
CRISIL Ratings (2024b)	to Mar-2024	Vehicle, MFI, Two-Wheeler
CRISIL Ratings (2024c)	to Jun-2024	Vehicle, MFI, Two-Wheeler
CRISIL Ratings (2024d)	to Sep-2024	Two-Wheeler, Mortgage
CRISIL Ratings (2025a)	to Dec-2024	Vehicle, MFI, SME, Personal Loans, Two-Wheeler, Mortgage
CRISIL Ratings (2025c)	to Mar-2025	SME, Mortgage
CRISIL Ratings (2025d)	to Jun-2025	MFI, SME, Personal Loans, Mortgage
CRISIL Ratings (2026a)	to Dec-2025	Vehicle
CRISIL Ratings (2026c)	to Jun-2026	Vehicle, Mortgage, MFI, Personal Loans

Variables

For asset class i in month t, the LEVEL is the published median MCR. To remove month-to-month noise, a three-month average is computed as A(i,t) = [MCR(i,t) + MCR(i,t−1) + MCR(i,t−2)] / 3. The DIRECTION is the change in this average over one quarter, D(i,t) = A(i,t) − A(i,t−3). For example, the microfinance average for December 2023–February 2024 (97.67 per cent) was 1.33 points below that for September–November 2023 (99.00 per cent), so D = −1.33. The placebo variable is the raw monthly change, MCR(i,t) − MCR(i,t−1). The outcome for H2 is the mean MCR over the following three months. For H3, a class is classed as stressed when its MCR is below 95 per cent, which is below the 97–99 per cent range that CRISIL describes as normal, and a direction signal is triggered when D ≤ −1 point.

METHODS

H1 was tested with one-way ANOVA, supported by a Kruskal-Wallis test that does not assume normality. H2 was tested with fixed-effects (within) regressions in which each asset class keeps its own normal level: model M1 uses only the current level, M2 adds direction and M3 replaces direction with the placebo. Classical standard errors are reported alongside errors clustered by asset class, bearing in mind that six clusters are few (Cameron et al., 2008; Petersen, 2009). A partial F-test measures the extra contribution of direction. For an honest forecast test, the models were estimated on April 2023–December 2024 only and then used to forecast January 2025 onwards (Diebold & Mariano, 1995). H3 follows the signals approach: among months in which a class was still healthy, signal occurrence was cross-tabulated against whether the class became stressed within three months, giving hit rates, false-alarm rates and noise-to-signal ratios. Every calculation was built as visible spreadsheet formulas and independently reproduced in Python; both gave identical results.

FINDINGS

Market Context and Differences Between Asset Classes

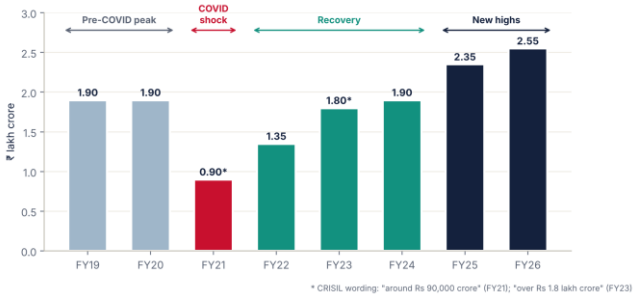

Figure 1. Indian securitisation volume, FY2019–FY2026 (₹ lakh crore)

*Source: CRISIL Ratings (2022, 2023, 2024a, 2025b, 2026b). *CRISIL describes FY2021 as "around Rs 90,000 crore" and FY2023 as "over Rs 1.8 lakh crore".*

Securitisation volume dropped by 52.6 per cent in the pandemic year, recovered by 50 per cent the following year and set fresh records in FY2025 and FY2026 (Figure 1). Over FY2019–FY2026 the compound annual growth rate was 4.3 per cent; measured from the FY2021 low it was 23.2

per cent. Vehicle loans formed the largest share of volume (40–47 per cent), while microfinance fell from 16 per cent of volume in FY2024 to 11 per cent in FY2025—the year its pools came under pressure.

Note: One-way ANOVA $F(5, 176) = 18.44$, $p = 1.05 \times 10^{-14}$, $\eta^2 = 0.344$; Kruskal-Wallis $H = 89.1$, $p < 0.001$.

Table 2. Median MCR (%) by asset class, April 2023 – June 2026

Asset class	n	Mean	SD	Min	Max	Months below 95%
Mortgage	32	98.88	0.66	97	100	0
Vehicle	38	98.68	1.09	97	101	0
Two-wheeler	21	98.57	0.93	97	101	0
Personal loans	35	96.29	1.13	94	99	1
Small business (SME)	18	95.72	1.99	92	99	4
Microfinance	38	94.21	5.17	83	100	12
All classes	182	97.02	3.14	83	101	17

Source: CRISIL Ratings (2024b–2026c); author's compilation. Blank cells: no value published.

Collection behaviour varied a great deal by asset class (Table 2, Figure 2), so H1 is supported: the asset class alone accounts for about a third of all variation. Mortgage, vehicle and two-wheeler pools collected close to 99 per cent month after month with little spread. Microfinance moved from 100 to 83 per cent and stayed below 95 per cent for twelve months.



Figure 2. Median MCR by asset class and month

Information Content of Direction

Table 3. Fixed-effects regressions of next-quarter mean MCR

	M1: Level	M2: Level + direction	M3: Level + monthly change
Current MCR	0.716*** (0.050)	0.595*** (0.053)	0.707*** (0.052)
Direction	—	0.353*** (0.072)	—
Monthly change (placebo)	—	—	0.073 (0.097)
R^2 (with class effects)	0.802	0.834	0.803
Adjusted R^2	0.793	0.825	0.792
Within R^2	0.613	0.675	0.615
RMSE, in-sample (points)	1.516	1.396	1.519
RMSE, out-of-sample (points)	2.187	2.030	—
Observations / classes	134 / 6	134 / 6	134 / 6

*Note: Classical standard errors in brackets; *** $p < 0.001$. Partial $F(1, 126) = 23.91$, $p = 3.0 \times 10^{-6}$ for adding direction. With asset-class clustering, direction stays significant ($p < 0.001$) and the placebo does not ($p = 0.77$). Out-of-sample: estimated on April 2023–December 2024 ($n = 74$); forecast January 2025 onwards ($n = 60$).*

Today's level carries strongly into the next quarter, yet direction remains positive and highly significant once the level is held constant (Table 3). A one-point fall in direction is followed by next-quarter collections about 0.35 points lower than the level alone would suggest. Including direction raises R^2 by 3.2 points, lowers in-sample error by 8 per cent and lowers out-of-sample error by 7.2 per cent. The placebo result matters for interpretation: the unsmoothed monthly change adds nothing, so the useful information lies in the smoothed quarterly movement. H2 is supported.

Lead Time of Direction Signals

Table 4. Performance of alternative signals (119 healthy asset-class-months)

Signal	Hit rate	False-alarm rate	Noise-to-signal	Precision
Monthly change ≤ −1 point	23.1%	30.2%	1.31	8.6%
Direction ≤ −1 point	61.5%	15.1%	0.25	33.3%
Level below 97%	84.6%	19.8%	0.23	34.4%
Level below 97% and direction ≤ −1 point	46.2%	4.7%	0.10	54.5%

Note: Stress means the MCR falls below 95% within three months. A noise-to-signal ratio below one indicates a useful signal.

Source: CRISIL Ratings (2024b–2026c); author's calculations.

Unsmoothed monthly changes perform worse than chance as a warning (noise-to-signal 1.31). Direction is informative (0.25), and combining it with a level threshold gives the cleanest signal of all: the false-alarm rate falls from 19.8 to 4.7 per cent and the noise-to-signal ratio to 0.10 (Table 4). In microfinance, direction first dropped below −1 point in February 2024, when collections still stood at 97 per cent; collections then fell below 95 per cent in June 2024—a lead of four months (Figure 3). In small-business pools the lead was three months. A short dip in personal-loan collections to 94 per cent in January 2026 was not anticipated. H3 is therefore supported for the asset classes that actually went through stress.

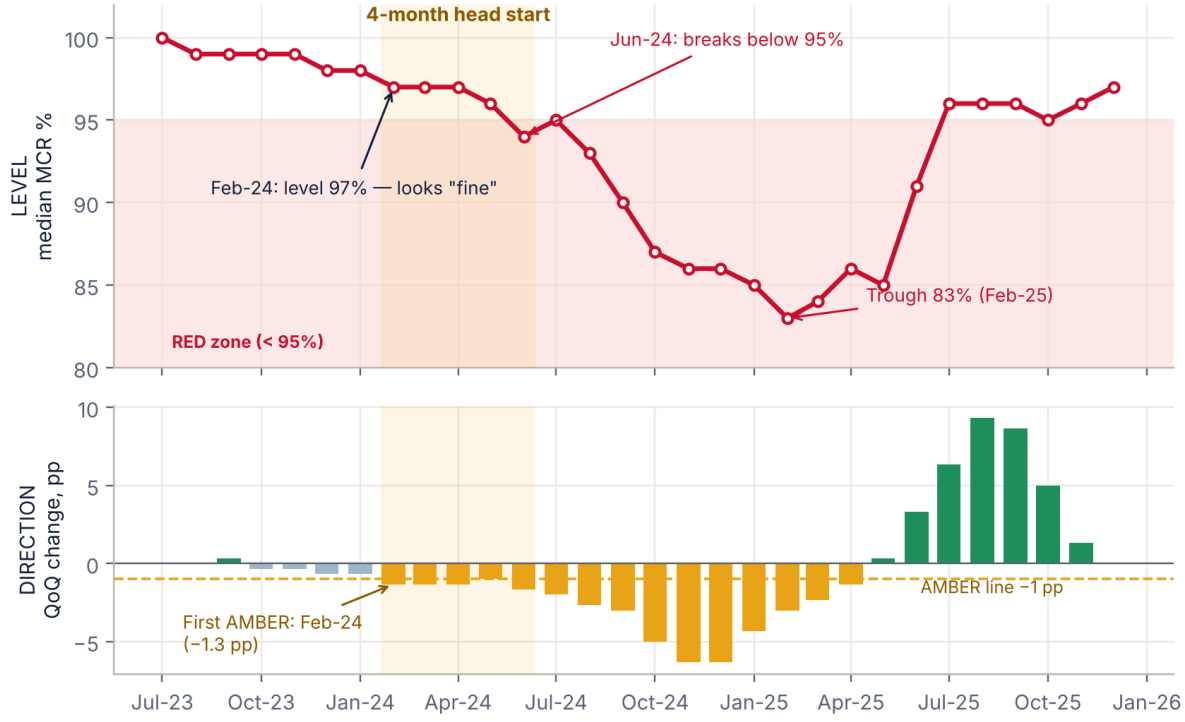

Figure 3. Microfinance pools: level of collections (top) and direction (bottom)

Robustness and Structural Protection

Results held when thresholds were changed: tightening the direction trigger to −1.5 or −2 points lowered false alarms to 5.7 and 2.8 per cent respectively, at the expense of hit rate, and no single threshold drove the conclusions. A balanced 2024 sub-panel taken from one report produced the same ranking of asset classes. When microfinance was excluded, the direction coefficient fell to 0.011 ($p = 0.90$), showing that in calm asset classes there is little decline to detect. On the structural side, CRISIL reported in five successive reports covering June 2024 to June 2025 that no microfinance pool had used its cash collateral and that three-month collections stayed above the median threshold collection ratio (CRISIL Ratings, 2024c, 2024d, 2025a, 2025c, 2025d). A 17-point fall in the typical pool's collections was thus absorbed inside the structures.

DISCUSSION

The results carry the message of Demyanyk and Van Hemert (2011) into an emerging-market setting: deterioration was visible in public performance data before it became plain to

see. The trend in collections, once smoothed, deserves as much attention as their level. For investors in PTCs, a monthly green–amber–red reading for each asset class, calculated from freely available reports, offers an inexpensive first screen. An amber reading should lead to a closer look at credit enhancement relative to the threshold collection ratio rather than to an immediate sale, since the 2024–25 episode showed that well-built pools can absorb a sizeable shock. For originators, applying the same reading to their own books offers an early prompt to tighten lending and collection practices. For rating agencies and supervisors, the findings support the publication of smoothed series and machine-readable pool data, a direction already signalled by the Securities and Exchange Board of India's (2025) circular on periodic disclosure for securitised debt instruments. The finding that direction adds little in calm classes is consistent with good monitor design: an alarm that stays quiet when nothing is wrong is more credible when it does sound.

CONCLUSION

Summary. Using a newly assembled and internally verified panel of 182 asset-class-months, this study finds that the direction of collections in Indian securitised pools carries forward-looking information beyond their level, that it anticipated the 2024 microfinance stress by four months, and that reading level and direction together cuts false alarms by about three-quarters. **Implications.** The Securitization X-Ray is simple enough to run in a spreadsheet and transparent enough for an investment or rating committee to audit, making it a practical complement to detailed pool analysis and to credit ratings. **Limitations.** The analysis relies on asset-class medians rather than individual pools, on whole-number values as printed, and on CRISIL-rated PTC pools alone; the sample contains one major and one mild stress episode, and inference clustered on six classes should be read with care. **Future scope.** A transaction-level panel built from CRISIL's pool tables—covering cumulative collection ratios, delinquency, cash-collateral use and threshold ratios—pooled across rating agencies, would allow the X-Ray to be tested pool by pool and, once data are large enough, compared with machine-learning forecasts.

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