A Project Report

On

Strategic Credit Risk Analytics: Portfolio Evolution, Migration, and Stress Testing

Under the supervision of

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Code Link: FRAM_Group 46_Google Colab.ipynb (All attached with the mail)
Ratings Data Sheet (grp46.xlsx): Data assigned to Group-46

Exploratory Data Analysis

Rating Composition Trend

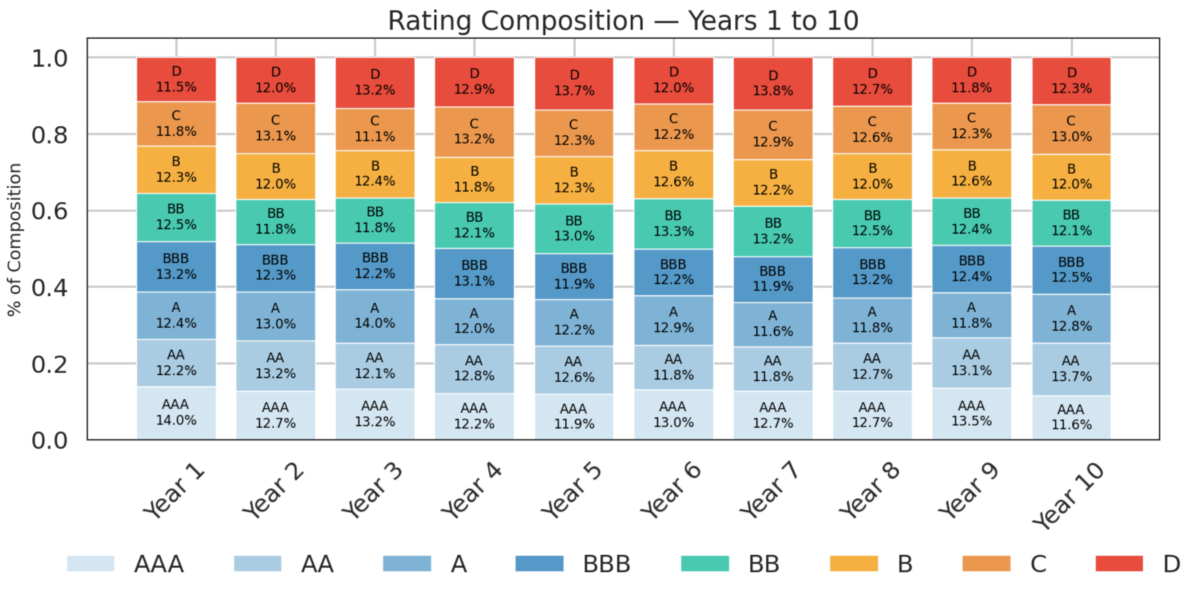

Fig 1: Stacked Rating Composition (Years 1–10)

The portfolio exhibits exceptionally **stable distribution** across all eight rating classes (AAA–D), each maintaining **~11–14%** exposure annually. Investment Grade (AAA–BBB) and Sub-Investment Grade (BB–D) each hold **~50%**, indicating a balanced risk stance and consistent underwriting discipline, exhibiting a risk-averse portfolio exposure.

The **absence of structural shifts** across the decade highlights low idiosyncratic concentration risk and implies that changes in portfolio risk are driven primarily by **migration patterns**, not portfolio rebalancing. This stability supports predictable Expected Loss (EL) behaviour and **reduces exposure to rating-bucket volatility**.

Rating Drift Dynamics (RDI)

Average rating migration fluctuates within a narrow band (approximately **–0.08 to +0.10** notches, **Fig. 2**), reflecting a cyclical credit environment rather than long-term deterioration.

Key stress points include **Year 2→3** (mild negative drift) and **Year 7→8** (sharpest decline). Recoveries in **Year 3→4** and **Year 6→7** offset these periods, demonstrating **mean-reversion** and **resilience** in obligor credit quality.

Overall, the drift pattern indicates short-term volatility but long-term credit stability, reinforcing that provisioning and capital buffers should account for cyclical migration rather than directional downgrades.

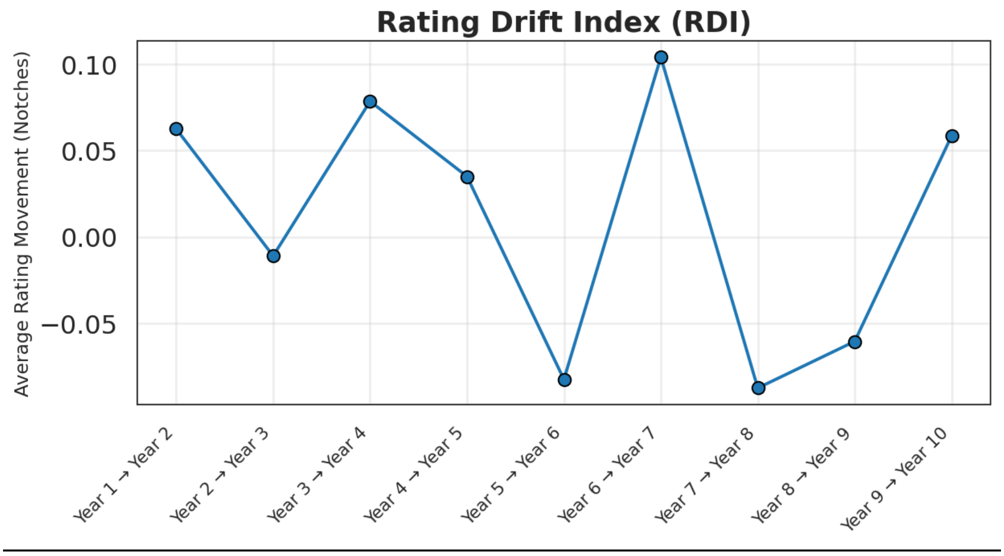

Fig 2: Rating Drift Index (RDI)

Portfolio Concentration (HHI)

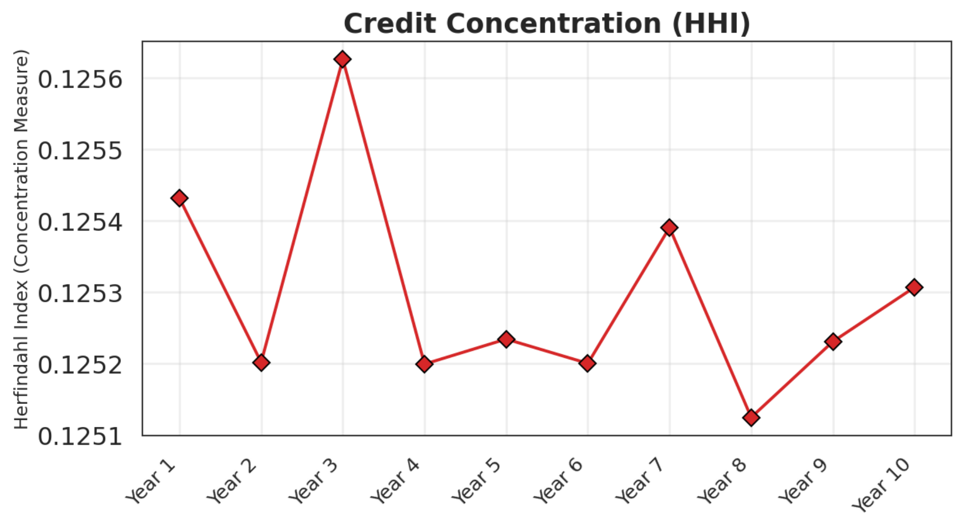

Fig 3: Credit Concentration (HHI)

The Herfindahl–Hirschman Index remains tightly clustered between **0.1251 and 0.1256**, signalling high diversification and negligible concentration in any single rating category.

Importantly, the HHI remains stable even during negative drift years, implying that downgrades are distributed, not clustered. This reduces sensitivity to migration shocks, supports stable EL trajectories, and enhances the portfolio's structural risk absorption.

Expected Loss Modelling

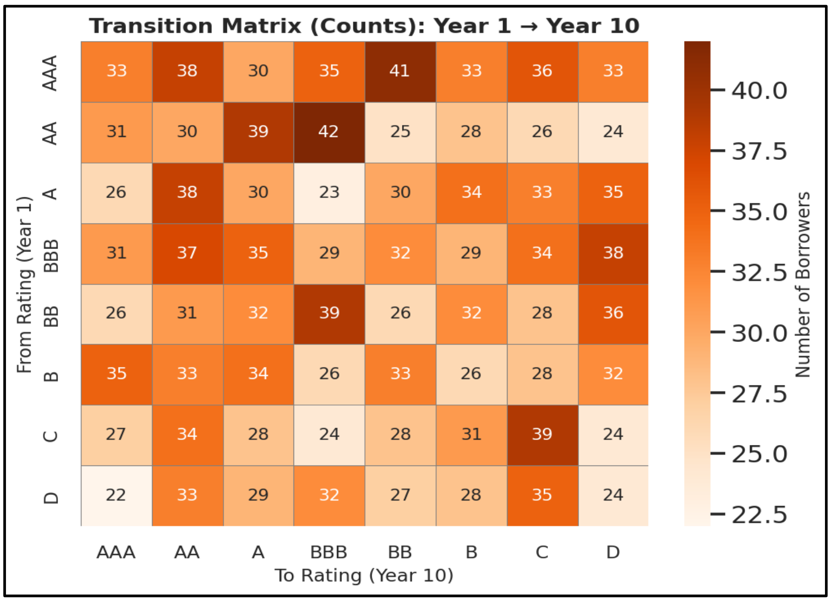

Fig 4: Rating Migration Heat Map

The **Transition Matrix (Year 1 → Year 10)** shows broadly distributed migrations with no single absorbing state and non-dominant diagonal counts, confirming significant rating mobility and supporting a **through-the-cycle** credit view. The **10-Year Cumulative Transition Matrix (Counts)** tracks borrower movement from Year 1 → 10, highlighting long-term deterioration. The absolute **highest migration is the multi-notch downgrade of 42 borrowers from AAA to BBB**. The lowest count is 22 borrowers moving from D to AAA. This implies the portfolio has a high structural long-term risk and low credit resilience. The multi-notch downgrades demonstrate that capital reserves must be aggressively set aside to cover the unexpected severity and magnitude of future credit losses, as high-quality assets are not reliable long-term anchors.

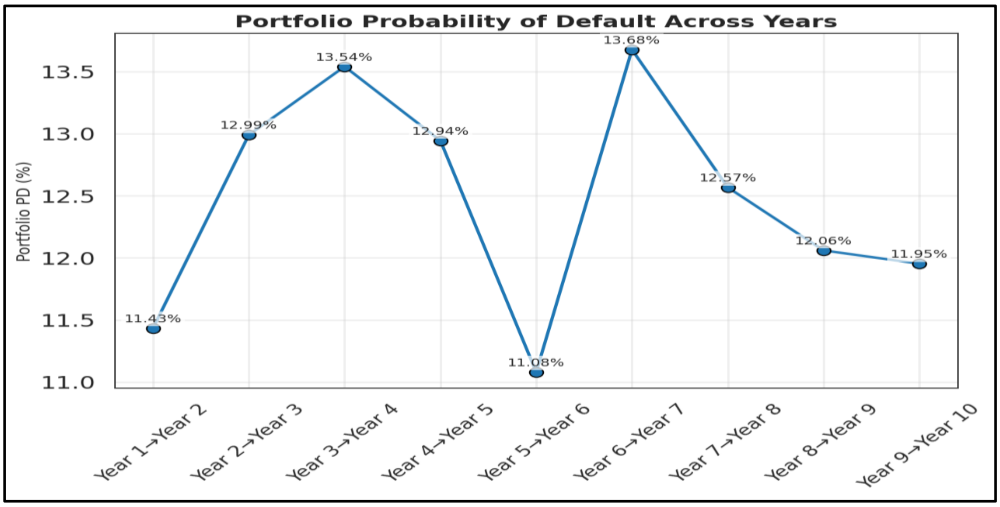

Fig 5: Probability of Default across years

Rating-level PDs derived from the transition matrices are **monotonic across the scale** (lowest for AAA, highest for D), confirming that the transition structure is economically consistent. Aggregating these individual rating PDs to the portfolio level shows that the total PD fluctuates significantly, moving in a relatively wide and impactful band between approximately **11.1%** and **13.7%** (**Fig. 5**).

This PD series is characterized as **cyclical**, not trending, which is consistent with the Rating Drift Index analysis that showed alternating periods of credit quality improvement and deterioration. This means the portfolio periodically experiences higher default risk but consistently reverts towards its long-run mean.

- The **lowest PD** is observed in **Year 5→6 (~11.1%)**, which indicates a brief credit environment where downgrades were minimized.
- The PD then peaks sharply in the subsequent period, **Year 6→7**, reaching **~13.68%**. A prior local high was also recorded around **Year 3→4** at **~13.54%**. These two peaks clearly point to at least **two distinct** stress episodes over the sample, where significant credit deterioration events occurred.

This **cyclical** PD trend is directly relevant to customers (investors/management) as it informs **dynamic capital allocation** and **risk-based pricing**, it shows that capital must be aggressively reserved for peak stress levels (like 13.7%) rather than assuming a stable average PD for loss forecasting.

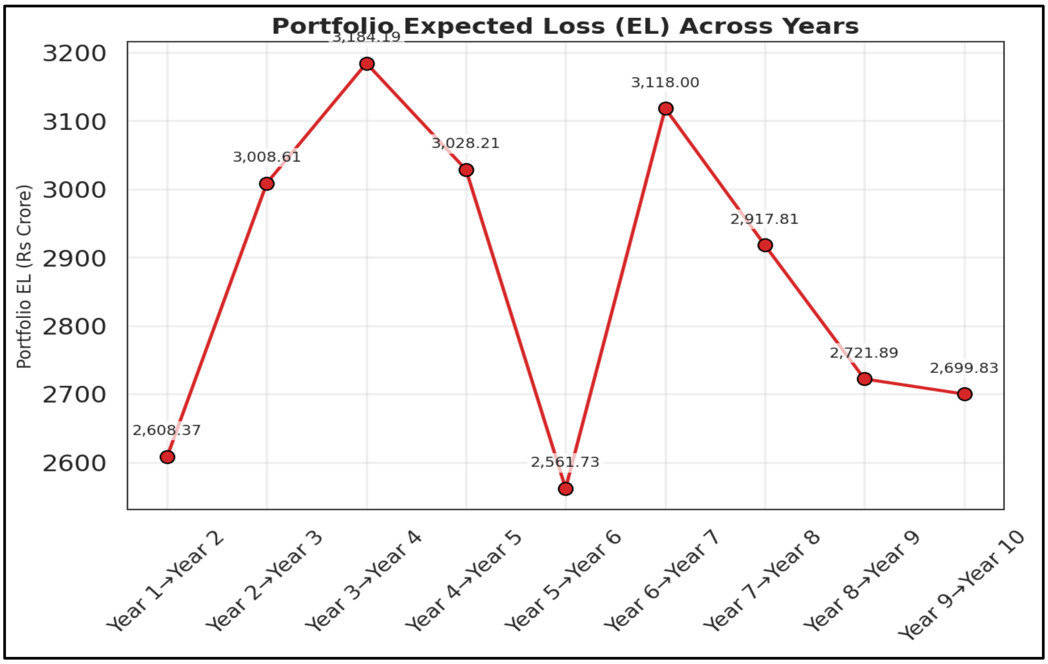

Fig 6: Expected Loss across years

Expected Loss (EL), calculated using rating-specific PDs, LGDs and EADs, shows a similar pattern (Fig. 6). Portfolio EL ranges from roughly **₹2,560 crore to ₹3,180 crore**, with peaks in **Year 3→4** and **Year 6→7**, coinciding with PD spikes. The amplitude of EL variation is **moderate relative to the total exposure base**, reflecting:

- **Stable EAD distribution** across ratings
- **Fixed LGD assumptions**, which prevent EL from escalating disproportionately even in higher-PD years.

In addition, the absence of sharp structural shifts in exposure composition suggests that **credit deterioration**, where observed, is transitory and primarily **macro-driven** rather than idiosyncratic. The alignment between PD spikes and EL movements further confirms that portfolio losses are responding predictably to **cyclical** stress rather than signalling model instability.

Overall, the PD and EL profiles indicate a portfolio that is **exposed to cyclical credit risk** but **not to structural deterioration**. Loss expectations rise in stressed years but remain within a **narrow, well-contained band**, implying that existing capital and provisioning frameworks should be adequate to absorb expected losses under normal business-cycle conditions.

Cumulative Probability of Default

The overall portfolio **Cumulative Probability of Default (CPD)** analysis shows the following:

Time Horizon	Portfolio CPD
End of Year 5	41.89%
End of Year 10	69.85%

The **CPD increases** from 41.89% at Year 5 to 69.85% at Year 10. This is the **expected trend** for a cumulative probability measure, as risk accumulates over time.

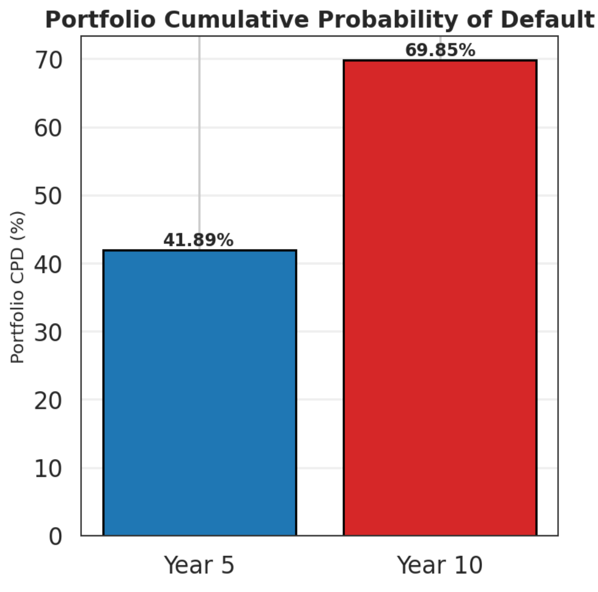

Fig 7: Cumulative Probability

This suggests that the **marginal default rate** during the second half of the period (Years 6-10) is substantial, confirming significant residual risk in the portfolio.

- **Marginal Default Rate (Years 6-10):** The probability of a default occurring between Year 5 and Year 10, given survival to Year 5, is calculated as **48.12%**.

Residual Risk and Risk Management

The marginal default rate of **48.12%** is a highly significant finding, indicating extreme **residual risk** in the portfolio's second half. This **Elevated Second-Half Risk** means exposures surviving five years still face an almost 50-50 chance of subsequent default, suggesting initial underwriting included a substantial number of highly cyclical or long-tenor, low-grade assets. Given this, **Stress Testing** is essential: Management must perform severe stress tests focusing on Year 5-10 macroeconomic downturns to quantify potential Loss Given Default (LGD). Furthermore, a **Refined Surveillance Strategy** is mandated; resources should intensely focus on the Year 5 surviving credit pool due to their demonstrably high aggregate risk, impacting capital requirements and provisioning.

Stress Testing Analysis

LGD Stress Scenario

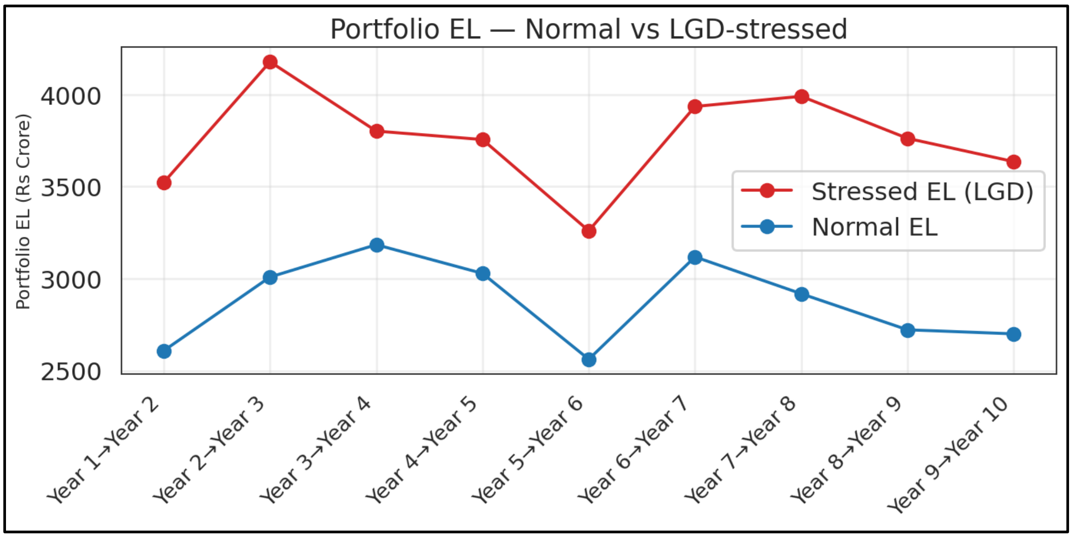

Fig 8: Comparison between Normal vs LGD Stressed

The chart illustrates how Expected Loss (EL) behaves under normal conditions compared to an LGD-stressed scenario across ten years. Under normal conditions, portfolio EL fluctuates between **₹2,561 crore (Year 5→6)** and **₹3,149 crore (Year 2→3)**, broadly mirroring movements in PD. In contrast, the stressed EL curve consistently sits higher, ranging from **₹3,239 crore (Year 6)** to **₹4,196 crore (Year 3)**. The stressed values exceed normal EL by roughly **₹700–1,200 crore** (**20%-38% higher**) each year, highlighting the portfolio's strong sensitivity to LGD shocks.

Years **3** and **7** show the widest divergence, with stressed EL more than **₹1,100 crore** above normal EL, signalling that periods of elevated PD combined with higher LGD have a compounding effect on total expected loss. Even in relatively stable years, such as **Years 8 – 10**, stressed EL remains **25%–35% higher**, indicating that LGD stress materially increases loss estimates even when PD is declining. The only temporary dip occurs in **Year 6**, where both **normal and stressed EL reach their lowest points**, consistent with an improved credit environment that temporarily reduces risk.

Overall, the chart demonstrates that the portfolio is **highly responsive to changes in LGD**, not just PD. While the normal EL curve shows cyclical movements driven by rating transitions, the stressed EL clearly reveals the magnitude of additional losses that emerge when recovery rates worsen, underscoring the critical role of LGD assumptions in credit risk modelling and stress testing.

Rating Migration Stress Scenario

The comparative bar chart provides a critical assessment of the portfolio's vulnerability by contrasting the Expected Loss (EL) under normal expectations with the loss projected under a defined stress scenario for the **Year 9 to Year 10 period**.

Under **Normal Conditions**, the portfolio EL is quantified at **₹2,699.83 crore**. This baseline figure represents the loss expectation derived from the standard transition matrix for the period, reflecting the typical flow of credit migration and default probabilities.

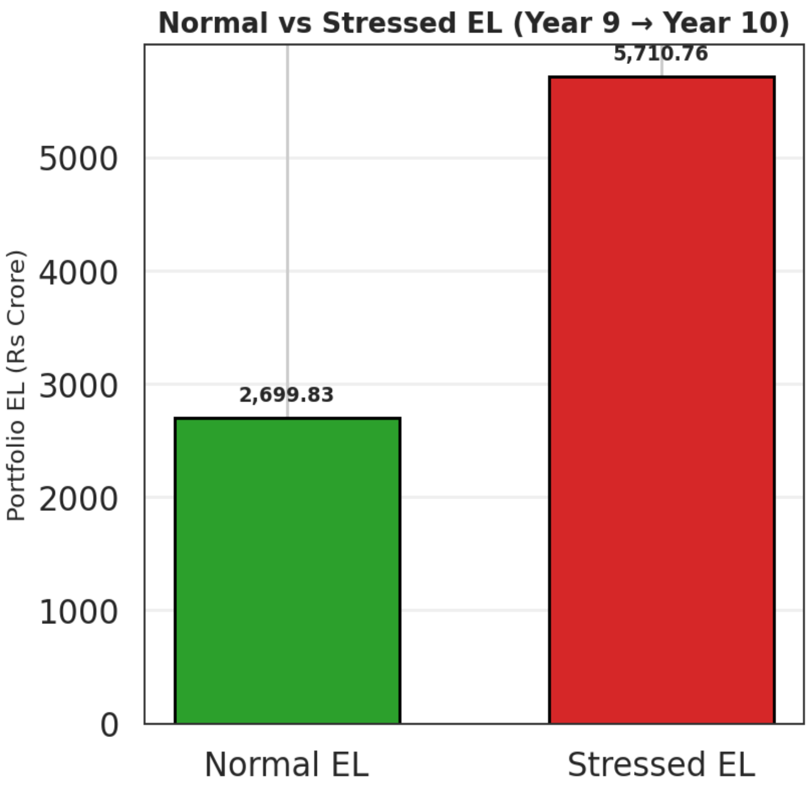

Fig 9: Normal Vs Stressed EL

However, the chart reveals a dramatic surge in risk when the **Stressed EL** scenario is applied, with the loss jumping to **₹5,710.76 crore**. This outcome is highly analytical: the stressed scenario which forces rating downgrades in the transition matrix causes the EL to increase by **around 112%**.

This profound increase directly establishes that the portfolio possesses **material sensitivity to severe credit deterioration**. The large spike confirms that concentrated **rating slippage**, which increases the Probability of Default (PD), acts as a **risk amplifier**, leading to a non-linear escalation of expected losses. This finding necessitates that capital planning and provisioning be aligned with this peak stressed figure, rather than the lower normal estimate, to ensure adequate resilience against systemic credit events.

Portfolio Risk Analytics

Credit Rating Stability Analysis

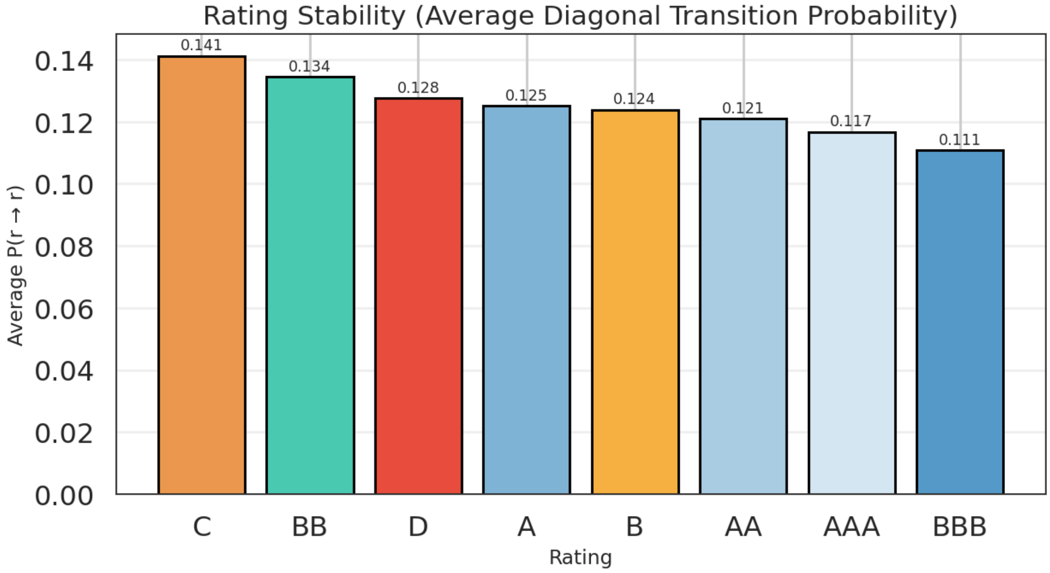

Fig 10: Rating Stability

- The rating category that exhibited the **most stability** over the years is **‘C’**, with an average ‘stay probability’ of **0.141**.
- This high stability in a lower-grade 'C' category (compared to AAA at 0.117) is **counter-intuitive**. Investment-grade assets are typically more stable. This suggests a need to **review the rating model's responsiveness** or the transition matrix methodology for potential biases.

Identification of Significant Portfolio Risk Shifts

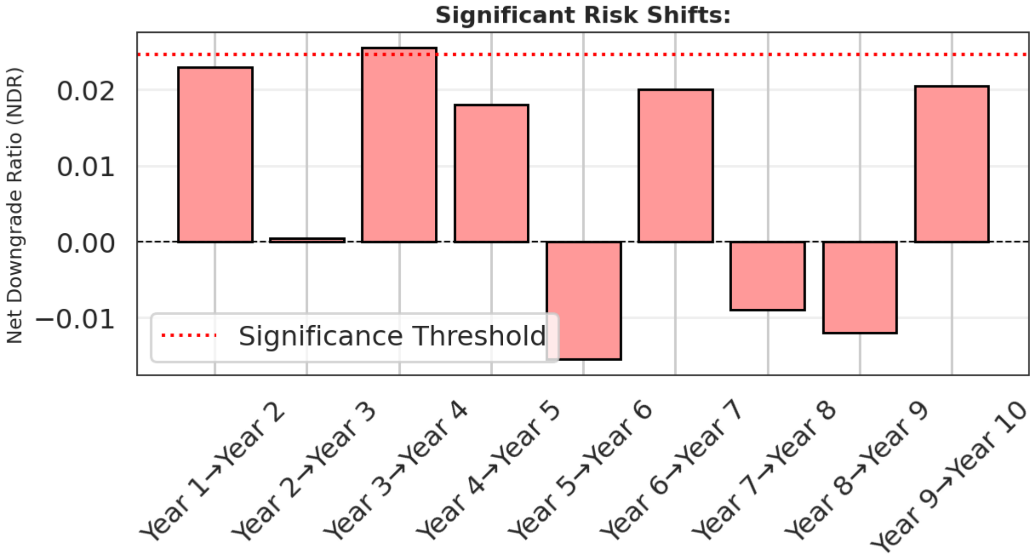

Fig 11: Net Downgrade Ratio

The analysis of portfolio credit dynamics identifies the period between **Year 3 → Year 4** as the single most critical risk shift, registering the **highest Net Downgrade Ratio (NDR)**, which uniquely exceeded the Significance Threshold. This event confirms a **systemic stress period** marked by significant credit deterioration (**more downgrades than upgrades**) and must be utilized immediately for **forward-looking stress testing** (e.g., under CECL/IFRS 9 guidelines) and **root cause analysis** to inform future risk management and capital planning.