October 23, 2026

Philip Barlow
Chair, Risk-Based Capital Investment Risk Evaluation (E) Working Group
National Association of Insurance Commissioners

Re: CLO Model documentation

Dear Chair Barlow:

On behalf of the C1 Subcommittee of the American Academy of Actuaries,[1] I would like to offer the attached report documenting our CLO Modeling work to date. We anticipate providing an addendum for additional sensitivity testing in the near future.

If you have any questions or would like to discuss this report further, please contact Marie Fabienne Amisial, life policy project manager (amisial@actuary.org).

Sincerely,

Stephen Smith, MAAA, FSA, CFA
Chairperson, C1 Subcommittee
American Academy of Actuaries

[1] The American Academy of Actuaries is a 20,000-member professional association whose mission is to serve the public and the U.S. actuarial profession. For 60 years, the Academy has assisted public policymakers on all levels by providing leadership, objective expertise, and actuarial advice on risk and financial security issues. The Academy also sets qualification, practice, and professionalism standards for actuaries in the United States.



OCTOBER 2026

Model Construction and Development of RBC C-1 CLO Factors

A report prepared for the NAIC by
American Academy of Actuaries
C-1 Subcommittee

American Academy of Actuaries
actuary.org

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Special thanks to Davis Parks for his support.

The American Academy of Actuaries is a 20,000-member professional association whose mission is to serve the public and the U.S. actuarial profession. For 60 years, the Academy has assisted public policymakers on all levels by providing leadership, objective expertise, and actuarial advice on risk and financial security issues. The Academy also sets qualification, practice, and professionalism standards for actuaries in the United States.

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October 2026

Any references to current laws, regulations, or practice guidelines are correct as of the date of publication.

October 2026

Model Construction and Development of RBC C-1 CLO Factors

A report prepared for the NAIC by the American Academy of Actuaries' C-1 Subcommittee

Executive Summary

This paper presents the methodology developed by the **American Academy of Actuaries**[1] **(Academy)** C-1 Subcommittee for estimating **risk-based capital (RBC) C-1** Factors for **collateralized loan obligation (CLO)** debt and equity tranches held by U.S. life insurance companies.

C-1 Factors are promulgated by the **National Association of Insurance Commissioners (NAIC)** and are a component of **RBC.** RBC is an estimate of an insurance company's risk and indicates the minimum level of surplus required to remain solvent in a tail scenario. C-1 Factors specifically approximate credit risk on invested assets.

CLOs are **structured financial products** that pool together loans and repackage the risks to investors through **tranching**. Accordingly, they present distinct analytical challenges relative to corporate bonds. Losses at the tranche level are a nonlinear function of collateral credit performance, especially in tail risk scenarios. Structural features of a CLO (attachment and detachment points, reinvestment periods, coverage tests, etc.) cause severity-given-loss to vary across deals and across tranches. These factors make it inappropriate to apply corporate C-1 Factors directly to similarly rated CLO tranches.

Starting in 2022, the NAIC Structured Securities Group (SSG) developed its own model for C-1 Factors that relied on Moody's CDOnet to project cash flows for individual CLO deals without accounting for CLO security ratings. Conversely, current (pre-2026) bond factors are assigned by credit rating,[2] as derived from a credit analysis performed by the American Council of Life Insurers (ACLI) and Moody's Analytics (MA). The Academy seeks to reconcile these two approaches by incorporating the ACLI/MA bond model (ACLI/MA Bond Model) and only making adaptations where CLOs fundamentally differ from bonds.

When developing and proposing C-1 Factors for an asset class, the Academy posits that new factors should only be applied to asset classes whose risk profiles are fundamentally dissimilar from existing

[1] The American Academy of Actuaries is a 20,000-member professional association whose mission is to serve the public and the U.S. actuarial profession. For 60 years, the Academy has assisted public policymakers on all levels by providing leadership, objective expertise, and actuarial advice on risk and financial security issues. The Academy also sets qualification, practice, and professionalism standards for actuaries in the United States.

[2] Factors are assigned by NAIC designation which, for both corporate bonds and CLOs, typically follows the credit ratings through the filing-exempt process.

modeled asset classes (e.g., corporate bonds). Then, it must be determined if sufficient data exists to model those unique risks. Finally, it must be determined if comparable attributes can adequately summarize an asset's risk level within an asset class without individual modeling. A **comparable attribute** is an easily calculated and easily verifiable attribute of an asset. For example, credit ratings (from Moody's, S&P, etc.) are used as comparable attributes for corporate bond C-1 Factors since credit ratings are widespread, verifiable, and explanatory.

Because CLO tranching creates a distinct risk profile from corporate bonds and because the underlying loans serving as collateral are well documented with robust data, the Academy concludes that modeling C-1 Factors is feasible. The Academy proceeds with several guiding principles, including: proposed factors should materially improve the ability to **identify weakly capitalized insurers;** factors should reflect the **impact of statutory accounting principles (SAP);** and **equal risks should receive equal treatment.**

The approach developed by the Academy accomplishes these goals through four integrated steps: (1) modeling collateral credit risk consistent with the corporate bond methodology, (2) projecting CLO cash flows with CDOnet, consistent with SSG modeling, (3) converting tranche-level tail losses into C-1 capital factors via a 90th percentile CTE estimate (Raw C-1 Factors), and (4) identifying comparable attributes that drive **"Modeled C-1 Factors."**

The collateral modeling inherits the framework used for bond C-1 Factors. The Academy adopts the same default rate assumptions by issuer rating and the same default correlation assumptions. The bond model assumes a **Gaussian copula distribution** with **10% correlation** in defaults. As sensitivity tests, the Academy considered the impact of utilizing a Clayton copula and the impact of changing the correlation assumption to 5% or 20%. Such changes would have dramatically changed the C-1 Factors adopted for bonds,[3] so the Academy retained the same methodology to avoid discrepancies in assumptions.

Four primary changes were made from the bond model. First, **the Academy removed the economic state component** from recovery rates. In the bond model, a Markov chain is used to simulate expansionary and contractionary economies, within which different recovery rate distributions are used. The Academy finds that this component of the model has a negligible impact on the final C-1 Factors for bonds and does not justify the extra model complexity. Second, **the Academy uses recovery rate distributions specific to loans** since loan recoveries are generally higher than bond recoveries due to seniority protections. Two distributions are used, one for senior loans and another for non-seniors. Third, **the Academy models the full loan universe at once** while the bond model derives base factors by rating. Cross-rating diversification is critical to CLO modeling since CLOs reduce risk in senior tranches through diversification. Fourth, the bond model simulates 10,000 scenarios and derives C-1 from the 96th percentile. The Academy runs 10,000 simulations but identifies 17 tail scenarios (90th percentile to 99.99th percentile) to estimate the **conditional tail expectation beyond the 90th percentile (CTE90).**

The resulting simulated defaults and recoveries are passed through CDOnet, which generates cash flows based upon modeling assumptions and specific CLO deal documentation (on rules for reinvestment, overcollateralization tests, etc.). The resulting cash flows are used to estimate maximum post-tax deficiency for each CLO as a proportion of 2024 year-end balance. Each security has 17 modeled C-1 Factors which are averaged together using **Riemann sums** to estimate the average risk beyond the 90th percentile. These averages for each CLO constitute the Raw C-1 Factors.

Modeled C-1 Factors are determined **through an ordinary least squares (OLS) framework**. By regressing Raw C-1 Factors at the security level against comparable attributes, average Modeled C-1 Factors can be derived from model coefficients. Through statistical testing, the Academy concludes that **credit**

[3] For example, see Appendix B where an increase to 20% correlation more than doubles the estimated C-1 Factor for some lower-rated corporate bond categories.

ratings (i.e., from S&P, Fitch, Moody's, KBRA, and DBRS) provide material information about an asset's tail risk. Additionally, for CLO debt tranches rated Baa3 and below, **tranche thickness** (defined as the difference between detachment and attachment point) provides additional information about tail risk. Finally, the Academy concludes that tail risk decreases as CLOs approach maturity.[4]

To maintain consistency with the ACLI/MA Bond Model, the Academy's approach normalizes all securities to have an average time remaining in the reinvestment period, thus making C-1 Factors **horizon-neutral.** Additionally, the Academy observes that initial Modeled C-1 Factors do not increase monotonically for CLOs rated A3 and above, due to limitations of data credibility (specifically, lack of heterogeneity in the endogenous factors). For A3 securities, the Academy uses **Akaike Model Averaging** to credibility-weight competing model outcomes. For A2 and above, the Academy applies an **isotonic regression** to force monotonicity and resolve credibility concerns.

The most subordinate component of a CLO is the equity tranche, also called the **residual tranche**. The equity tranche is not entitled to scheduled cash flows but experiences levered returns from excess net income produced by the underlying loans. Under the **practical expedient** approach to accounting for residual tranches, SAP requires insurers to treat cash flows as principal payments, thus reducing book value. From an accounting standpoint, reductions in book value are conservative because they reduce total asset value and, consequently, reduce capital and surplus (assets minus liabilities). An alternative method called **allowable earned yield** operates similarly except that it requires only a portion of cash flows to be treated as principal payments, with the rest treated as income.

Consistent with the guiding principles, the Academy accounts for SAP and models both practices from the cash flows produced by CDOnet. The Academy ultimately elects to use practical expedient accounting for final factors because it depends on fewer modeling assumptions, which leads to more credible results. The current post-tax C-1 Factor for residual tranches is 35.55%. Also consistent with guiding principles, the Academy concludes that the modeled factors do not significantly deviate from 35.55%, so **no change is recommended** (only significant changes with high confidence justify modifications in factors).

[4] CLO practitioners have advised that this relationship may be backwards. They advise that the market treats CLOs with a longer remaining reinvestment horizon as less risky because the CLO manager can offset poor credit experience through active management and buying loans at a discount. The Academy model is structurally not designed to capture this effect because it assumes all loans are purchased at par and does not account for any value created from active management by the CLO manager.

The resulting CLO after-tax C-1 Factors are:

Rating	Proposed After-Tax C-1 Factors	
	Thickness > 4%	Thickness ≤ 4%
Aaa	**0.03%**	
Aa1	**0.04%**	
Aa2	**0.04%**	
Aa3	**0.04%**	
A1	**0.14%**	
A2	**0.14%**	
A3	**0.80%**	
Baa1	**1.81%**	
Baa2	**2.70%**	
Baa3	**2.73%**	**12.52%**
Ba1	**12.59%**	**22.39%**
Ba2	**20.93%**	**30.72%**
Ba3	**23.28%**	**33.08%**
B1	**26.04%**	**35.84%**
B2	**35.20%**	**44.99%**
B3	**47.32%**	**57.12%**
Caa1	**48.12%**	**57.92%**
Caa2	**55.20%**	**64.99%**
Caa3	**70.82%**	**80.61%**
Residual Tranche	**35.55%**	

The Academy also models a **portfolio adjustment factor (PAF)** for CLOs. Within the bond C-1 framework, base factors are scaled by PAF, which is calculated from the number of unique issuers. In concept, this represents the increased risk of asset concentration (conversely, the reduced risk from issuer diversification).

Due to modeling limitations, the Academy was unable to model PAF directly for CLOs. But consistent with the goal of equal treatment for equal risks, the Academy calculates PAF based on the diversification of underlying collateral. The Academy's proposed base CLO factors are derived from an analysis of the full CLO universe, so any actual portfolio of CLOs will be *less* diversified than the base C-1 Factors indicate.

To estimate an appropriate PAF, the Academy first identifies the full-universe PAF—the PAF that would be applied to an insurer who owns the entire universe of loans underlying the modeled CLOs. Then, the Academy samples sub-portfolios of CLOs (e.g., a portfolio containing two CLOs, three CLOs, four CLOs, etc.) and estimates the distribution of unique loan issuers within each sub-portfolio and estimates the distribution of the corresponding PAFs. Because unique CLOs invest in many of the same underlying loan issuers, adding CLOs to a portfolio increases diversification at a decreasing rate. For each sub-portfolio of CLOs, the Academy estimates **relative PAF** as the ratio of sub-portfolio PAF to full-universe PAF and identifies the median value.

The following factors are recommended:

# of Unique CLOs	**Proposed Portfolio Adjustment Factor**
1	**1.3907**
2	**1.2222**
3	**1.1586**
4	**1.1254**
5	**1.1060**
6	**1.0926**
7	**1.0831**
8	**1.0760**
9	**1.0704**
10	**1.0661**
11+	**1.0000**

The Academy **alternatively recommends a PAF of 1.0** for all insurers. The first guiding principle of the analysis is that the purpose of RBC is to identify potentially weakly capitalized insurers. By analyzing 2024 year-end statutory filings, the Academy observes that insurers who own six or fewer CLOs are either invested solely in Aa3 and above CLOs (for which the PAF adjustment would *at most* increase factors by 0.01%) *or* have 1% or less of total assets invested in CLOs. PAF quickly plateaus to 1.0, so any additional granularity would have a *minor impact* on required capital, industry wide.

Finally, the Academy analyzes the impact of proposed factors on regulatory arbitrage. An ongoing concern is that a loan portfolio could be restructured into a CLO and an insurer owning every tranche of the CLO (i.e., the **vertical slice**) could receive a lower average C-1 Factor than if they owned the same loans directly (despite retaining the exact same risk). The Academy finds that on average the **proposed factors do not create regulatory arbitrage.**

Differences in loan factors and CLO factors are explained by two factors: conservative statutory residual tranche accounting and PAF. Because SAP requires reduction in book value for residual tranches of CLOs but not for loans, a vertical slice CLO will have *less total asset value* for an insurer than would the full portfolio of underlying loans. Furthermore, the underlying loan pool is well diversified across issuers, so the base factors for loans must be adjusted by the corresponding PAF to create an apples-to-apples comparison. The proposed vertical slice CLO C-1 Factors are lower than a simple average of bond C-1 Factors for the underlying loans, but this is **fully explained** by **the reduced asset value** and **issuer diversification benefit.**

Acknowledgments

ACLI—for use of the C-1 corporate bond model developed by Moody's for ACLI

Moody's—for access to CLO deal data, collateral data, historical default rate data, CDOnet, and discussions with credit and insurance professionals

S&P—for historical recovery data and discussions with insurance and structured finance analytical professionals

Bridgeway Analytics—for discussions on credit modeling, structured finance, and help in understanding the ACLI & Moody's corporate bond model

NAIC staff at SSG—for hands-on modeling advice and running CDOnet

NAIC accounting staff—for guidance on CLO statutory accounting and reporting

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1 Introduction

Risk-based capital (RBC) is a regulatory framework established by the National Association of Insurance Commissioners (NAIC) that requires insurance companies to hold a minimum level of capital in proportion to the riskiness of their assets and liabilities. RBC metrics are used to monitor insurer solvency and identify companies potentially at risk of insolvency. C-1 (asset default risk) is the component of the RBC formula that captures the risk of loss from invested asset defaults or market value declines. Required base capital charges are applied at the asset level based on factors that vary by asset class and credit quality. Additional factors are applied to account for issuer diversification and concentration.

The current framework for C-1 bond factors for fixed income securities was initially implemented in 1994, based on default experience from 1970–1990. These factors remained in place for over two decades before the American Academy of Actuaries (Academy) C-1 Working Group undertook a formal effort to modernize them. The Academy published an initial proposal in August 2015[5] and followed with an updated recommendation in October 2017. These proposals were revised multiple times through 2021 in response to stakeholder feedback and the signing of the Tax Cuts and Jobs Act in 2017 (TCJA), with adjustments including updates to the discount rate and the corporate tax rate assumption (from 35% to 21%).

The American Council of Life Insurers (ACLI), in conjunction with the NAIC, commissioned Moody's Analytics (MA or Moody's) to develop an independent set of C-1 bond factors. In February 2021, MA assessed the Academy's proposed revisions, and by April and May 2021, MA published its formal report: "Revisions to the RBC C-1 Bond Factors."[6] The credit model used to derive such C-1 bond factors (the ACLI/MA Bond Model) uses Moody's historical default rates (1983–2020) and recovery rates (1987–2020), a Markov-chain economic state transition matrix, a Gaussian copula with 90% idiosyncratic and 10% systematic variance, a 96th-percentile value-at-risk (VaR96) risk metric, and a 2.74% post-tax discounting assumption. The model also assumes a "risk premium" equal to half a standard deviation above the mean of the present value of losses. This is roughly equivalent to assuming that an insurance company's reserves are sufficient to cover a 70th percentile loss (discounted to present value) on any given security; the RBC charge seeks to represent the proportion of additional balance needed to cover a loss up to the 96th percentile.

The ACLI/MA proposal became the adopted set of C-1 bond factors beginning in 2021.

With the bond factor methodology established, attention turned to structured securities, CLOs in particular. The NAIC's Structured Securities Group (SSG) conducted earlier CLO-specific work through its CLO Ad Hoc Group, developing an approach to model CLO tranche cash flows. However, the SSG model is inconsistent with the ACLI/MA Bond Model. The Academy's C-1 Subcommittee (C-1 SC) was charged with building a CLO C-1 modeling framework that preserved the structural integrity of the ACLI/MA Bond Model while adapting it to address the unique characteristics of CLO collateral and cash flow mechanics. The Academy's approach synthesizes key aspects of the SSG model with the modeling framework followed by the ACLI/MA Bond Model.

The Academy's CLO C-1 modeling framework (CLO C-1 Modeling Framework)—outlined in this document—has been developed in close collaboration with the SSG and draws on resources from Moody's Analytics (CLO deal data, collateral data, historical default rates, the CDOnet cash flow engine, and discussions with experts), S&P (historical recovery data and discussions with experts), and Bridgeway Analytics (credit modeling guidance and support in understanding the ACLI/MA Bond Model).

[5] *Model Construction and Development of RBC Factors for Fixed Income Securities for the NAIC's Life Risk-Based Capital Formula*; American Academy of Actuaries; Aug. 3, 2015.
[6] Revisions to the RBC C1 Bond Factors Prepared for the NAIC and the ACLI; Moody's Analytics; April 2021.

A formal description of the CLO C-1 Modeling Framework was presented to the Risk-Based Capital Investment Risk and Evaluation Working Group (RBC IRE) on September 8, 2025.[7] A status update including sensitivity testing was provided to regulators on December 15, 2025,[8] at which point two key milestones had been accomplished: finalizing key model assumptions and identifying the full universe of CLO deals to be modeled. Proposed C-1 Final Factors for CLO debt tranches were presented on March 2, 2026.[9] The proposal for residual tranches and portfolio adjustment factors (PAF) was presented on May 6, 2026.[10] The Academy's proposed base factors were adopted by the Risk-Based Capital Investment Risk and Evaluation Working Group (RBC IRE) on June 23, 2026,[11] while the PAF adjustment was set to 1.0. The same adoptions were then made by the Capital Adequacy Task Force on June 30, 2026,[12] and finally by the Financial Condition (E) Committee on July 8, 2026.[13] Changes are effective for year-end 2026.

2 Background on CLOs

A CLO is a structured finance vehicle with two core functions. First, it provides a large, stable source of investor demand for leveraged corporate loans, helping companies access credit. Second, it repackages a diversified pool of loans into securities with different risk/return profiles, so each investor can choose their preferred exposure. The transformation of typically below-investment-grade loans into investment-grade CLO debt tranches is the mechanism for increasing investor demand for leveraged corporate loans. The CLO manager (typically an asset management firm) earns management fees by actively overseeing the portfolio on behalf of investors. The essential mechanism behind the structure is tranching: pooling many loans together and slicing the resulting cash flows so that some investors bear the first losses and earn higher yields, while other investors are protected and earn lower yields.

To accomplish this, a special purpose vehicle (SPV) is created to own the loan portfolio. An SPV is a legally isolated entity that issues multiple classes of debt securities (tranches) plus equity to investors; the proceeds are used to purchase a portfolio of leveraged loans. The portfolio typically includes 200–800 unique assets issued by 100–400 corporations (see Appendix A). The SPV's liabilities (debt tranches plus equity) must equal the value of its assets (the loans plus cash held for distribution or reinvestment). The collateralized loans typically account for ~96% of total CLO face value.

Tranches are stacked from most senior (AAA) to most junior (equity). Senior tranches have the first claim on cash flows and the last exposure to losses. Equity sustains initial losses but has the most upside gain when the underlying loans mature without default. Most leveraged loans pay floating rates (historically, London Interbank Offered Rate, or LIBOR, plus a spread; now Secured Overnight Financing Rate, or SOFR, plus a spread). CLO debt tranches are similarly structured as floating-rate instruments, each paying SOFR plus a spread that is set at issuance and reflects the tranche's credit risk. AAA tranches pay the tightest spread; BB tranches (or lower-rated tranches, if they exist in the structure) pay the widest. The equity tranche receives no fixed coupon—it receives whatever cash remains after all debt tranches are paid (subject to overcollateralization and interest coverage tests as described below), making its return highly sensitive to portfolio performance.

The manager selects loans during a warehouse period before the CLO closes and continues building the portfolio afterward. Loan selection is governed by eligibility criteria written into the CLO indenture,

[7] C1SC Update on CLO C-1 Factors Modeling; American Academy of Actuaries; Sept. 8, 2025.
[8] C-1 Subcommittee Update on CLO C-1 Factors Modeling; American Academy of Actuaries; Dec. 15, 2025.
[9] C-1 Subcommittee Update on CLO C-1 Factors Modeling; American Academy of Actuaries; March 2, 2026.
[10] C-1 Subcommittee Update on CLO C-1 Factors Modeling—Residual Tranches and Portfolio Adjustment Factors; American Academy of Actuaries; May 6, 2026.
[11] Risk-Based Capital Investment Risk and Evaluation (E) Working Group Agenda and Meeting Materials; NAIC; June 23, 2026.
[12] Capital Adequacy (E) Task Force Agenda and Meeting Materials; NAIC; June 30, 2026.
[13] Financial Condition (E) Committee Agenda and Meeting Materials; NAIC; July 8, 2026.

including:

- Minimum loan size and maximum single-issuer concentration
- Minimum/maximum weighted average spread (WAS)
- Maximum weighted average rating factor (WARF)
- Industry concentration limits
- Minimum diversity score

These constraints ensure the portfolio remains diversified and within the risk parameters promised to investors at issuance.

CLOs also have a reinvestment period, typically ~5 years. During this time, principal repayments from loans—and principal recovered during a default—are recycled back into new loan purchases rather than returned to investors. This keeps the portfolio fully invested and extends the period over which equity can earn excess spread. The manager actively trades loans throughout this window. Once the reinvestment period ends, principal proceeds are used to pay down tranches sequentially, starting with the most senior (AAA). This is known as the sequential paydown. The CLO winds down as loans mature or are sold and tranches are retired. The legal final maturity is typically 10–13 years from closing, the date the SPV is legally constituted.

When a loan in the portfolio defaults, the portfolio recovers a fraction of par value. If the total value of the remaining portfolio exceeds principal and interest obligations to the CLO debt holders during the reinvestment period, the recovered amount is reinvested. Otherwise, losses are sustained:

- First, equity absorbs the loss; its net asset value is reduced.
- Once equity is wiped out, losses begin to impair the most junior debt tranche (typically BB-rated).
- Losses continue working up the stack (BB → BBB → A → AA → AAA) as cumulative defaults grow.

Credit enhancement (CE) is the amount of the capital structure subordinate to a given tranche. This is formalized through the concepts of attachment and detachment points. A tranche's **attachment point** is the cumulative loss level at which it begins to suffer losses; its **detachment point** is the level at which it is completely wiped out. For example, a BBB tranche with a 12% attachment point and an 18% detachment point begins losing principal only after 12% of the collateral pool has been lost and is fully exhausted when 18% has been lost. The equity tranche always has an attachment point of 0% since it sustains the first dollar lost.

Beyond attachment and detachment points, CLOs are governed by a set of portfolio quality and coverage tests that constrain the manager and protect senior investors. The most important of these are:

WARF: A Moody's-derived numerical measure of the average credit quality of the loan portfolio. Higher WARF corresponds to lower average quality. Each rating maps to a numerical factor (e.g., Ba3 ≈ 1,766; B1 ≈ 2,220; B2 ≈ 2,720; B3 ≈ 3,490), and the portfolio WARF is the loan balance-weighted average of these factors. The indenture sets a maximum WARF the manager cannot breach. CLOs generally have a WARF of ~2,800. Other rating agencies maintain comparable measures of collateral credit quality.

WAS: The average spread over SOFR earned by the portfolio, weighted by loan balance. A minimum WAS is required to ensure sufficient interest income to pay all tranches.

Weighted Average Life (WAL): The weighted average time until loan principal is repaid. A maximum WAL test prevents the portfolio from becoming too long-dated.

Overcollateralization (OC) Tests: These compare the par value of the collateral to the outstanding balance of a given tranche and all tranches senior to it:

$$\text{OC Ratio} = \frac{\text{Collateral Par Value}}{\text{Outstanding Balance of Covered Tranches}}$$

Each tranche has its own OC test with a minimum threshold (e.g., AAA OC ≥ 120%). If the test fails, cash that would otherwise flow to junior tranches or equity is diverted to pay down senior tranches until the test is cured.

Interest Coverage (IC) Tests: These compare interest income from the collateral to interest due on the covered tranches:

$$\text{IC Ratio} = \frac{\text{Interest Income from Collateral}}{\text{Interest Due on Covered Tranches}}$$

A failing IC test similarly redirects cash away from junior investors toward senior paydown. Together, OC and IC tests act as automatic de-leveraging mechanisms that protect senior investors when the portfolio takes losses.

Cash flows from the loan portfolio are distributed in strict **priority of payments** (the "waterfall"): trustee and administrative fees are paid first, followed by the senior management fee and then interest on the AAA tranche, continuing down through AA, A, BBB, and BB tranches (and below, if they exist). OC/IC cure payments are made if any tests are failing, followed by the subordinate management fee, and finally equity distributions. Principal is paid sequentially (AAA first) after the reinvestment period ends.

A **typical CLO** at issuance has the following characteristics:

Attribute	Typical Value
Collateral type	First-lien senior secured leveraged loans
Number of loans	300–900
Portfolio par size	$400M – $1B+
Weighted Average Rating Factor (WARF)	2,600 – 3,400 (roughly B/B+ average quality)
Weighted Average Spread (WAS)	SOFR + 350–425 bps
Weighted Average Recovery Rate	65–70%
Reinvestment Period	4–5 years
Legal Final Maturity	10–13 years from closing
Weighted Average Life at Close	5–7 years

Shown here is an illustrative structure:

Tranche	Rating	Thickness (% of Capital Structure)	Attachment Point	Detachment Point	Spread (SOFR+)
AAA	AAA	64%	36%	100%	130 bps
AA	AA	12%	24%	36%	140 bps
A	A	6%	18%	24%	160 bps
BBB	BBB	6%	12%	18%	260 bps
BB	BB	4%	8%	12%	500 bps
Equity	NR	8%	0%	8%	NA

3 Modeling Approach

3.1 Guiding Principles[14] for Structured Securities RBC

The Academy undertook this project to develop a principled, analytically rigorous framework for determining C-1 risk-based capital (RBC) charges applicable to structured securities, with an initial focus on collateralized loan obligations (CLOs). The methodology described herein was developed in accordance with six foundational principles, each reflecting the Academy's considered judgment about the appropriate role of RBC in insurance solvency regulation and the particular characteristics of structured credit instruments. These principles are the result of iterative edits between the Academy and RBC IRE, with RBC IRE ultimately endorsing the principles as laid out below.

The principles are:

1. The purpose of RBC is to help regulators identify potentially weakly capitalized insurers; therefore, changes that have a small impact on RBC ratios may not justify a change to the RBC formula.

2. Emerging risks require regulatory scrutiny.

3. C-1 requirements reflect the impact of risk on statutory surplus. Changes in accounting treatment will affect RBC.

4. C-1 requirements for a given tranche align with that tranche's risk.

5. C-1 requirements on asset-backed securities (ABS) should treat the collateral as a dynamic pool of assets.

6. C-1 requirements for ABS should be calibrated to different risk measures where appropriate.

Together, these six principles define the analytical boundaries within which the C-1 capital charge model was constructed and ensure that the resulting framework is both technically sound and consistent with the broader objectives of insurance solvency regulation in the United States.

The first principle establishes an important threshold consideration: RBC functions as a coarse regulatory filter designed to identify potentially weakly capitalized insurers, not as a precise measure of economic risk. Accordingly, methodological refinements are only warranted where they produce a material impact on RBC ratios across a meaningful portion of the industry. Changes with limited systemic reach may not justify modifications to the RBC formula, even if they improve precision at the individual company level.

The second principle recognizes that RBC operates within a broader regulatory ecosystem. Tools such as Own Risk and Solvency Assessment (ORSA), asset adequacy testing, actuarial guidelines and supervisory examinations complement the RBC framework and should be considered in tandem when evaluating emerging risks. RBC refinements are intended to address material solvency concerns and should be principle-driven and structurally neutral with respect to prevailing market conditions.

[14] These principles were developed and endorsed by RBC IRE in 2023, prior to the creation of the RBC Model Governance Task Force (MoGo). In the time since, MoGo has established an overarching set of principles to guide not just RBC for structured securities but all of RBC. One of these principles has been cited often during discussions of CLO C-1 Factors, namely "equal capital for equal risk." In the context of the six principles described herein, "equal capital for equal risk" most closely aligns with principle #4.

The third principle anchors C-1 requirements to the statutory accounting framework. Because C-1 capital is designed to protect statutory surplus, the treatment of a given asset must reflect how gains and losses flow through the statutory balance sheet. Assets carried at fair value embed market price volatility directly into surplus, which supports a higher C-1 requirement relative to assets carried at amortized cost. Consistent with this principle, C-1 charges for rated, unimpaired debt tranches are calibrated to expected credit losses only, while residual tranches—which are often held at a carry value well below their net asset value—must also incorporate this conservative accounting.

The fourth principle requires that C-1 charges align with the actual risk profile of each individual tranche. The absence of a rating on the underlying collateral is not, in itself, determinative of the appropriate capital charge; what matters is whether a credit rating provider (CRP) has performed a granular assessment of the collateral pool that is reflected in the tranche rating. This principle guards against both over- and under-capitalization arising from categorical assumptions about collateral quality.

The fifth principle reflects the dynamic nature of managed CLO structures. Unlike static bond portfolios, CLO collateral pools evolve over time as managers reinvest principal proceeds and respond to changing credit conditions. The methodology therefore treats the collateral pool as a dynamic asset base, incorporating the effects of future trading activity across a range of economic scenarios. Importantly, C-1 requirements are not reduced to account for idiosyncratic manager outperformance—capital charges reflect the risk inherent in the asset class, not hypothetical outperformance.

The sixth principle addresses the calibration of risk measures. The risk profile of structured securities differs materially from that of conventional bonds, exhibiting non-linear loss characteristics and pronounced tail risk. The Academy therefore determined that conditional tail expectation (CTE), rather than value-at-risk, is the more appropriate basis for calibrating C-1 requirements for CLOs, as it captures the severity of adverse outcomes in the tail of the loss distribution. While RBC neutrality between a CLO tranche and a direct investment in the underlying collateral pool is a useful reference point, strict neutrality is not a design requirement; a reasonable and defensible relationship between the two is sufficient.

3.2 Determining the Appropriate C-1 Modeling Approach

RBC IRE endorsed a framework proposed by the Academy where three threshold conditions must be satisfied for C-1 capital charges to be addressed for a given asset class:

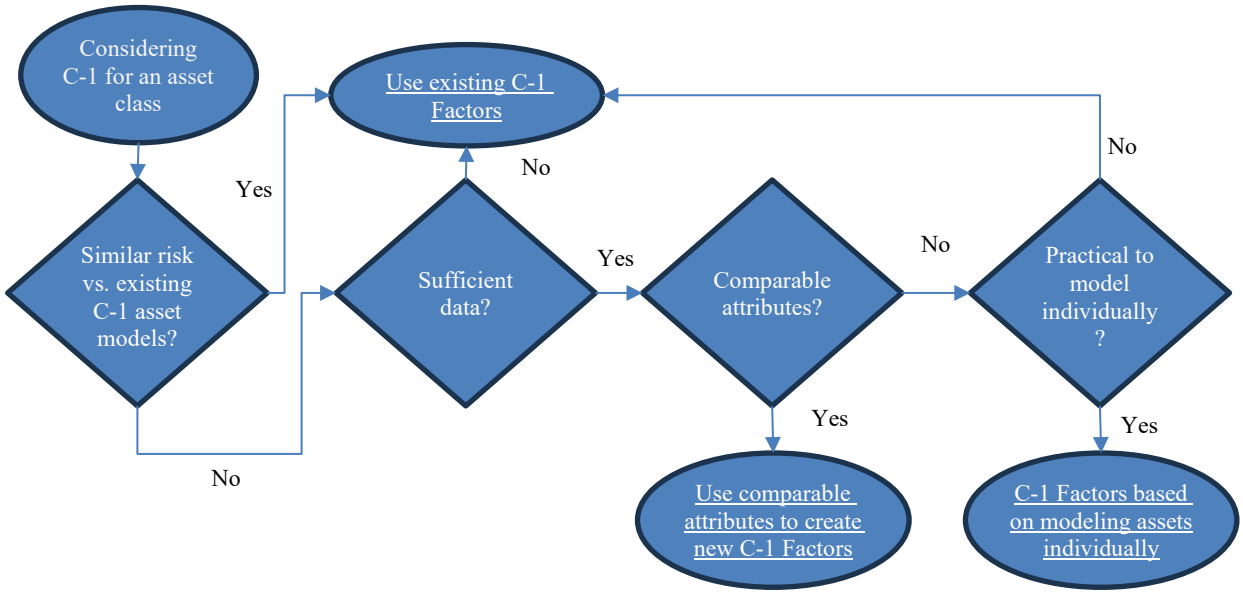
1. The asset class must be sufficiently material in terms of industry-wide insurer allocations to justify the analytical investment;

2. The risks in question must be genuine C-1 credit and solvency risks rather than, for example, illiquidity risk more appropriately addressed through other regulatory mechanisms; and

3. The incremental benefit of developing a tailored methodology must outweigh the operational and regulatory complexity it introduces.

Only when all three conditions are met does the flowchart logic described below proceed to determine the form that modeling should take.

Figure 1 - C-1 Modeling Flowchart



The C-1 Modeling Flowchart (Figure 1) poses a sequential series of decisions, each of which narrows the range of appropriate methodological treatments.

The first decision asks whether the risk profile of the asset class under review is sufficiently similar to that of an asset class already covered by an existing C-1 model. Where the answer is yes, the analysis proceeds directly to consider whether the attributes of the new asset class are comparable to those of the existing one. If the risk profile is materially different—as is the case where, for example, tail risk escalates more steeply as credit quality declines—the existing model is not a reliable proxy, and the analysis advances to consider whether sufficient data exist to support the construction of a new framework.

The second decision, reached only when similarity to an existing model has been ruled out, evaluates data sufficiency. C-1 modeling requires an adequate empirical foundation; without sufficiently robust data, risk cannot be reliably calibrated.

The third decision is applicable when an existing model has been ruled out and when this asset class has sufficient data to support a new one. It asks whether the assets within the class share comparable attributes that allow them to be grouped into risk buckets. Where such attributes exist, a factor-based approach is viable: assets are sorted into buckets based on a shared observable characteristic, and a single capital factor is assigned to each bucket. For rated securities, the CRP rating is the natural bucketing attribute, analogous to the designation system used for corporate bonds. For unrated asset classes, proxy metrics may substitute; commercial mortgage loans, for instance, are bucketed using debt service coverage ratios and loan-to-value ratios rather than ratings. Depending on the availability of comparable attributes, the result of this branch may be either the creation of new C-1 Factors or consideration of individual security modeling.

The fourth and final decision applies when neither existing factors nor a new risk-bucket framework can adequately capture the differentiation across assets within the class. Here, the flowchart asks whether individual security modeling is practically feasible. If so, assets are modeled on a deal-by-deal basis, producing security-specific capital requirements. This is the most granular and most resource-intensive treatment, so it is reserved for asset classes whose risk profiles are sufficiently heterogeneous that bucket-

level averaging would produce materially misleading capital signals. Non-agency residential and commercial mortgage-backed securities modeled by the Structured Securities Group represent canonical examples of this treatment. Where individual security modeling is neither practical nor technically feasible, no viable path through the flowchart exists—reinforcing why the threshold cost-benefit condition at the outset is an essential gatekeeping requirement. In such a case, the least bad option is to use an existing set of C-1 Factors. While this will not precisely capture risk, there is no feasible alternative approach that would.

In the case of CLOs, the analysis proceeds along the branch that produces a new set of risk-bucket factors. CLO tranches possess a risk profile that is fundamentally distinct from that of corporate bonds: loss severity in lower-rated tranches is disproportionately high, causing tail risk to escalate non-linearly with declining credit quality. These characteristics are not adequately captured by the existing corporate bond factor schedule, ruling out the first branch of the flowchart. However, the availability of CLO deal and collateral data—along with the analytical tractability of scenario-based cash flow modeling—supports the construction of a new factor schedule, rather than requiring the full operational burden of deal-level individual security modeling. In other words, the Academy seeks to identify comparable attributes and create new C-1 Factors rather than pursuing a framework that requires every security to be uniquely modeled at every RBC reporting date.

4 Data

4.1 Collateral Data Universe

The collateral data was provided by Moody's Analytics (MA). This data set consisted of all loans that underlie CLOs since 2003. The data was filtered down to observations in Q4 of 2024. MA's database includes snapshots of the collateral at multiple points throughout the year (Run Dates). CLO deals (i.e., the full CLO vertical slice of debt and equity) that were run multiple times in Q4 of 2024 were filtered so that only the most recent Run Date was kept. The resulting data set consisted of:

- 3,016 deals
- 7,702 unique loan issuers
- 1,256,415 collateral assets

This data set includes the following fields:

a) **BALANCE:** The total dollar amount invested in the asset

b) **SECURITY_TYPE:** Type of collateral, by balance:

SECURITY_TYPE	BALANCE ($)
Loan	1,101,739,982,146
Bond	66,513,764,479
DDL	6,533,788,946
RL	297,299,184
TRUPS	34,500,000
SN	25,000,000
SECMKTSP	20,000,000
Loan Participation	7,114,308
EQ	10,416
IO	161

c) **SECURITY_GROUP:** Group of collateral, by balance:

SECURITY_GROUP	BALANCE ($)
Loan	1,108,571,070,276
Bond	66,548,264,479
Other	52,114,469
Equity	10,416

d) **MATURITY:** Date that collateral matures.

e) **SENIORITY:** Loan-level seniority, by balance:[15]

SENIORITY	BALANCE ($)
Sr Sec	1,135,190,457,127
Sr Unsec	16,178,288,692
Second Lien	7,129,316,514
Subordinated Secured	216,209,645
Sr Sub	162,528,280
Mezz	8,845,226
Senior	7,678,983
Junior	1,623,571
Jr Mezz	947,912

f) **ISSUER_RATING:** Ratings from Moody's and S&P at the *issuer* level

g) **RATING:** Ratings from Moody's, S&P, and Fitch at the *asset* level

4.1.1 Standardizing Collateral Credit Ratings

Collateral credit ratings were processed and standardized to generate a single credit rating input used for collateral default modeling. Issuer rating is selected over asset rating given that the ACLI/MA Bond Model relies on issuer-level ratings. However, this requires preprocessing to address missing data and to address discrepancies between issuer- and asset-level ratings.

At the issuer level, Moody's and S&P ratings are provided. At the asset level, Moody's, S&P, and Fitch are all provided. As shown in the table below, only 87.7% (1 − 12.3%) of line items (weighted by balance) in the collateral have an issuer rating (either Moody's or S&P); 94.9% have at least one rating of the asset and 95.1% have a rating of either the asset or the asset's issuer.

Table 1 - Missing Ratings for Loans in CLO Collateral

	Aggregate Amounts		Proportion of Total Universe	
	Missing Count	Missing Balance	Missing Count	Missing Balance
Moody's Issuer Rating	268,436	301,770,262,361	21.5%	25.7%
S&P Issuer Rating	222,886	292,184,032,278	17.9%	24.9%
Moody's Asset Rating	59,693	111,797,066,545	4.8%	9.5%
S&P Asset Rating	73,728	129,876,556,972	5.9%	11.1%
Fitch Asset Rating	633,150	609,591,063,311	50.8%	51.9%
Both Issuer Ratings	93,582	144,091,822,029	7.5%	12.3%
All 3 Asset Ratings	28,878	59,630,883,740	2.3%	5.1%
All 5 Issuer and Asset Ratings	27,767	57,914,389,401	2.2%	4.9%

[15] Some assets do not have a recorded seniority. See Section 4.1.2.

First, the Academy observes that within the 87.7% of line items that have at least one issuer rating, 70.3% have a rating from both Moody's and S&P, and 26.4% have different ratings from the two agencies. In cases where the ratings differ, the lower of the two is assigned to the issuer, in line with NAIC designation assignment procedures.

Table 2 - Distribution of Assets with at Least One Issuer Rating

	Aggregate Amounts		Proportion of Total Universe	
	Count	Balance	Count	Balance
Both Issuer Ratings Present	849,435	725,308,977,789	73.5%	70.3%
Both Present but Disagree	330,227	272,465,561,216	28.6%	26.4%

Second, among the 2,901 unique issuers that have two ratings present in the collateral data universe, there are 584 issuers for which at least two assets have issuer ratings (the lower of Moody's and S&P) that differ from one another. The cause of this discrepancy is the Run Date. Each CLO has its collateral recorded periodically and the dates of recording happen at different points throughout the quarter. At least one CLO had its last Q4 2024 Run Date on October 2 and at least one CLO had its last Q4 2024 Run Date on December 31. To account for the cross-CLO discrepancies, the Academy standardizes the issuer ratings by recording only the *most recent* Run Date.

As an example, one issuer appears in the collateral data universe with 284 unique assets held across 139 CLO deals. These CLOs had their collateral recorded on 19 different dates during Q4 of 2024 (from November 5 to December 31). The assets recorded on November 5 have an A- issuer rating from S&P (no Moody's issuer rating). The assets recorded on November 20 or later have an issuer rating of A from S&P (still no issuer rating from Moody's). To standardize the ratings, the Academy looks at the issuer rating on December 31 (A, for the example presented) since that is the most up-to-date data and assigns that rating to all assets from the issuer.

Lastly, the Academy uses asset-level ratings to proxy issuer-level ratings where issuer rating is not available. As shown in the table above, a greater proportion of collateral has asset-level ratings than issuer-level ratings, so the asset-level ratings can be used as a proxy. However, the asset-level ratings and issuer-level ratings do not map 1:1. Because loans are predominantly first lien, they have higher recovery rates than unsecured debt. This can cause an asset to have a higher rating than the rating of its underlying issuer. For example, an issuer rated B by S&P could issue a loan rated B+ because it is senior to the issuer's unsecured debt.

To quantify this, the Academy filters the collateral data to all line items that have both an issuer rating and asset rating. Since there are ratings from three agencies at the asset level, the Academy assigns either the worst of two ratings or the median of three for the asset-level rating (using the worst of two for issuer-level rating). Converting these aggregated ratings to numbers (with Aaa equal to 1, Aa1 equal to 2, etc.), the Academy calculates the average issuer rating for each asset-level rating, weighting by balance. For all ratings B2 and above, the average issuer rating is either the same as or worse than the asset rating. This is consistent with the hypothesis that leveraged loans' issue ratings are on average higher than the issuer rating. Averaging across all asset ratings by balance, the average difference in rating is 0.09. This translates to: for a given asset rating, the issuer rating is on average 9% of a rating worse.

Table 3 - Distribution of Issuer Ratings per Existing Asset Rating

Letter Rating	Asset Rating	Average Issuer Rating	Difference
Aaa	1	1.56	0.56
Aa1	2	2.00	0.00
Aa2	3	3.00	0.00
Aa3	4	4.56	0.56
A1	5	6.34	1.34
A2	6	6.41	0.41
A3	7	7.04	0.04
Baa1	8	8.11	0.11
Baa2	9	9.41	0.41
Baa3	10	10.38	0.38
Ba1	11	11.57	0.57
Ba2	12	12.31	0.31
Ba3	13	13.23	0.23
B1	14	14.08	0.08
B2	15	15.15	0.15
B3	16	15.96	-0.04
Caa1	17	16.92	-0.08
Caa2	18	17.70	-0.30
Caa3	19	18.43	-0.57
Ca	20	19.02	-0.98
C	21	18.65	-2.35
D	22	21.50	-0.50
Total	14.79	14.88	0.09

Relying on this conclusion, the Academy groups all asset-level ratings by issuer—for the issuers that do not have any recorded issuer-level rating—and averages together all numeric asset ratings (either the worst of two or median of three). The average is weighted by balance, and the final rating number is set equal to the next whole number above the average. For example, if assets for an issuer are mostly rated B2 with some B1, with an average rating number of 14.8, the next whole number is 15, equivalent to a B2 rating.

For a given loan rating of B3 or lower, the average issuer rating is slightly higher. For example, for loans rated B3, the issuer rating is on average 0.04 notches higher. Despite this observation, the Academy decides to adjust all ratings equally for internal consistency. This results in additional conservatism for loans rated B3 and below for which issuer rating is not available.

4.1.2 Standardizing Tranche Seniority Levels

Because loan recoveries depend highly on seniority, the Academy uses one distribution for senior loan recovery rates and another for non-senior loan recoveries. After applying aforementioned filters, 98.3% of balance is senior debt. The remaining 1.7% is mapped to non-senior (including the line items with missing seniority data).

4.1.3 Data Exclusions

After standardizing collateral credit ratings, 71.0% of issuers have an assigned rating. This accounts for 97.3% of the collateral balance. Only 180 CLO deals have at least one debt security without any assigned issuer rating. Within these 180 deals, 35.2% of the collateral's balance is unrated. Due to the concentration of missing data in these deals, the Academy elects to exclude them from further analysis.

Of the remaining 2,835 CLO deals, 2,674 are classified as "CDO - High Yield CLO-Arbitrage Cash Flow." The data is further truncated to 2,674 deals to exclude all middle market loans given that the data set only covers a small share of the middle market universe. The remainder of this analysis applies only to

broadly syndicated loan (BSL) CLOs.

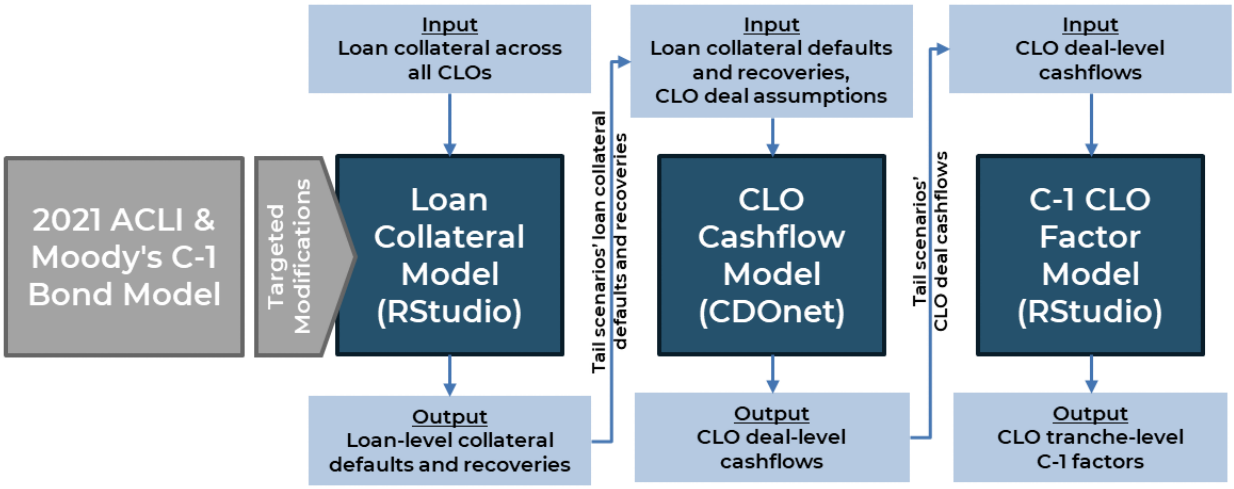
4.2 CLO Deal Data Universe

All deal-specific information (on tranche structure, interest and principal payments, reinvestment rules, etc.) is contained within CDOnet, courtesy of Moody's Analytics.

5 Assumptions and Methodology

The Academy estimates CLO tranche-level Raw C-1 Factors for the universe of CLO deals held by insurers using a 3-step modeling approach:

Figure 2 - Raw C-1 Factors 3-Step Modeling Approach



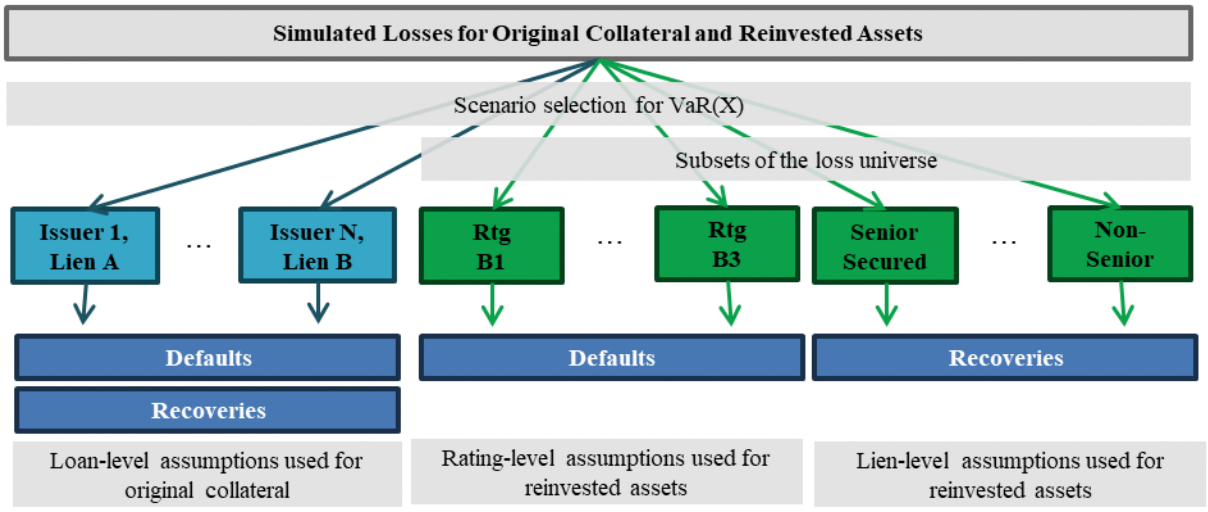
Raw C-1 Factors are unique to each CLO debt tranche. Modeled C-1 Factors are then derived using the Comparable Attributes Modeling Approach.

5.1 Raw C-1 Factors

5.1.1 Step 1—Loan Collateral Credit Model (Collateral Model)

The purpose of the Collateral Model is to produce loss input assumptions for the CDOnet Cash Flow Model. Assumptions are provided for the original collateral and for the reinvestment collateral. For original collateral, a vector of time-to-default and a vector of loss-given-default are provided for each security. For reinvested collateral, the Academy calculates vectors of default rates by rating and recovery rates by lien.

Figure 3 - Loan Collateral Model Overview



The Collateral Model generates 10,000 simulations, consistent with the ACLI/MA Bond Model. The simulations are 10-year loss projections where issuer default and loan recoveries are modeled stochastically for the full collateral universe. Present value (PV) of losses is calculated across the collateral for each scenario. For each scenario, the following assumption vectors are produced:

- For each unique combination of issuer and lien, default and recovery vectors.
- For each rating, default vectors.
- For each lien, recovery vectors.

The default and recovery assumption vectors for the unique combinations of issuer and lien are used for the original collateral present in the CLO deal universe as of Q4 2024. The default assumption vector by rating and recovery assumption vector by lien are used for reinvested assets.

5.1.1.1 Consistency with ACLI/MA Bond Model

When examining options for modeling collateral risk, the Academy preserved the ACLI/MA Bond Model where possible. However, certain fundamental changes needed to be made up front:

- **Switching from VaR96 to CTE90:** Bond losses are predominantly driven by idiosyncratic risks and their severity is diversified. CLOs, by contrast, suffer no losses until the attachment point is penetrated at which point defaults can quickly approach 100%. As a result, targeting one single percentile (like 96) could underestimate the tail risk for bonds that are first penetrated in a 97th percentile or worse scenario. To account for the fatter tail risk, the Academy concludes that switching from value-at-risk (VaR) to conditional tail expectation (CTE) is appropriate.

- **Removing economic state Markov chain:** The ACLI/MA Bond Model did not assume a constant recovery distribution; instead, it implemented two recovery rate distributions that are chosen by the economic state. The economic states are determined by a Markov chain where the economic state alternates between expanding and contracting (based on fixed conditional probabilities). Due to data limitations on loan recoveries, the economic state model was removed.

- **Sampling full-universe scenarios:** In the ACLI/MA Bond Model, a 96th percentile was chosen for each rating with the number of bonds determined by a representative insurer's portfolio. This approach accounts for diversification within ratings but not across ratings. However, C-1 is supposed to represent a security's contribution to total portfolio risk, not its own individual risk. This is crucial to CLO modeling because the CLO structure accounts for cross-rating diversification.

To quantify the effects of the first two changes, the Academy re-ran the ACLI/MA Bond Model to determine what the bond C-1 Factors would be if these two modeling decisions were made (see Appendix B). When comparing various CTEs, the Academy finds that CTE90 produces bond C-1 Factors most similar to the adopted VaR96 factors. The root mean squared error (RMSE) is 0.1%, indicating that bond factors would move around by a rough average of 10bps should the VaR96 be switched to CTE90. The simple average is a change of 0.01%, meaning that a switch from VaR96 to CTE90 would cause bond C-1 Factors to increase, on average, by only 1bp. It was impractical to quantify the impact of the third change due to computational constraints.

The Academy concludes that the switch from VaR96 to CTE90 better captures the tail risk of CLOs without causing a meaningful deviation from the bond model. Should the NAIC seek consistency across bond and structured factors, bond factors could be re-run with CTE90 without a significant average impact.

Regarding the economic states, re-running the ACLI/MA Bond Model with the assumption that the economic state is always expansionary lowers factors by 7bps on average with an RMSE of 17bps. For investment-grade (IG) bonds, both the absolute average change and RMSE are less than 1bp. The Academy was unable to procure recovery rates by economic states. Because the impact of the economic state assumption is minor in the ACLI/MA Bond Model, the Academy concludes that removing the economic states assumption does not cause the Collateral Model to meaningfully differ from the ACLI/MA Bond Model.

5.1.1.2 Defaults and Recoveries Assumptions

When modeling collateral risk, the Academy seeks continuity with the ACLI/MA Bond Model. Within that model, **defaults** are randomly sampled based on *issuer* rating (by an agency), using a probability mass function (PMF) by rating and years-from-rating. Moody's provided the PMF to the Academy, along with the accompanying code, written in R.

For **recovery rates**—the amount recovered during default as a proportion of par—the ACLI/MA Bond Model randomly samples rates under a PMF, where the recovery rates are separated into deciles (e.g., a recovery rate of 8% falls into the 0-10% recovery decile). There are 11 buckets since recoveries can fall into the >100% recovery bucket, should interest be recovered in addition to principal. When a bucket is selected via random sampling, the average value of that bucket is assigned as the security's recovery rate.

Since loans have security provisions, their recovery rates systematically differ from the recovery rates for unsecured bonds. The Academy replaced the recovery rate distribution with data provided by S&P in the same format (split into deciles, with a >100% bucket and with average rates per bucket). The Academy distinguishes senior from non-senior loans for the purpose of modeling recovery. These rates are presented in S&P's publication "Recovery Study (U.S.): Quantitative Easing, Low Yields, And Distressed Exchanges Have Boosted Bond Recoveries Since 2010."[16] The recovery rates for senior loans are proxied by Chart 10 ("First-Lien Term Loan Recovery Rate Histogram") and for non-senior loans are proxied by Chart 11 ("Second-Lien And Unsecured Term Loan Recovery Rate Histogram").

The Academy was unable to procure loan recovery rates by decile from Moody's, so S&P data was used

[16] Sign-in required for access.

instead. This could potentially introduce a discrepancy between the CLO Collateral Model and ACLI/MA Bond Model. S&P reports recovery rates as the ultimate amount recovered while Moody's reports recovery rates 30 days after default. Because CLO managers typically sell defaulted loans prior to recovery, this divergence may reduce the model's accuracy.

As a stress test, the Academy constructed a hypothetical distribution of recovery rates such that the average loss given default (LGD) for senior and non-senior loans match the average LGDs published by Moody's; the shape of the distribution was chosen to minimize difference from the S&P distribution using least-squares. The Collateral Model was run on six sample deals (see Appendix K, Sensitivity 5). Although the results are purely hypothetical given Moody's actual recovery rates were not available to the Academy, the stress test shows significant differences in the C-1 Factors.

5.1.1.3 Stochastic Loss Simulations

Consistent with the ACLI/MA Bond Model, the Academy runs 10,000 simulations that project losses over a 10-year horizon. The seed is set to 1 so that random numbers can be replicated. The full collateral is grouped by issuer. For each issuer, the cumulative probability of default distribution is appended in accordance with the issuer's rating. The default probabilities are identical to those used in the ACLI/MA Bond Model.

To accommodate CDOnet, the default probabilities are geometrically interpolated from year-end probabilities to month-end probabilities. These are then converted into one-month marginal probabilities.

As in the ACLI/MA Bond Model, a Gaussian copula is used with a 10% correlation assumption. In the ACLI/MA Bond Model, this involves sampling a random variable for each year from the standard normal distribution (the systematic risk) and one random variable for each line item and each year (the idiosyncratic risk). A default occurs for line item i if:

$$\sqrt{10\%} \times Z_{systematic} + \sqrt{90\%} \times Z^{i}_{idiosyncratic} \leq \Phi^{-1}(P^{i}_{default})$$

where Φ is the cumulative distribution function (CDF) for a standard normal variable. This is mathematically equivalent to sampling a default for each line item i with probability $P^{i}_{default}$ because the sum of two normal variables is normal; because the mean for both the systematic and idiosyncratic components is 0; and because the composite variance is $\left(\sqrt{10\%}\right)^2 + \left(\sqrt{90\%}\right)^2 = 100\% = 1$. In the ACLI/MA Bond Model, the defaults are sampled by year rather than month so the systematic components represent annual probabilities. To not over-diversify, the Collateral Model uses the same $Z_{systematic}$ factor for all 12 months in each year but a different idiosyncratic factor for each month. If a loan defaults, the year and month are recorded. Only the time of the first simulated default is recorded—the ACLI/MA Bond Model can simulate multiple defaults per line item since the model assumes that all defaulted bonds are replaced by identical bonds, paid for by surplus.

The Academy considered adjusting the correlation parameter since it may not be the case that loan and bond issuers have the same exposure to systematic risk. Supporting literature shows a variety of correlations and is not conclusive on an appropriate point estimate.[17] Qi et al. found that the correlation parameter ranges from 2% to 10% for B-rated bonds, depending on the time horizon. Meanwhile, Li and Chen found that the correlation for B-rated issuers can range from 2% to 51%, depending on the time horizon.[18] Consistency with the ACLI/MA Bond Model requires that any divergence from the ACLI/MA Bond Model should be justified by statistically significant differences between the bonds typically held by life insurers and loans

[17] "Default Correlation: Rating, Industry Ripple Effect, and Business Cycle"; *Applied Economics*; 2019.
[18] "The Domino Effect of Credit Defaults: Test of Asymmetric Default Correlations Using Realised Default Data"; *Applied Economics*; 2018.

typically held by CLOs. Because the academic literature on cross-issuer correlation is inconclusive, it is implausible that any alternative correlation is better than the ACLI/MA assumption of 10% with statistical significance.

To understand the impact of the assumption, the Academy ran a stress test on the ACLI/MA Bond Model with alternate correlation assumptions (0%, 5%, 20%, and 40%). The Academy found that the results are highly sensitive to this correlation assumption (see Appendix B). The resulting bond factors can change by nearly a factor of two or three when choosing 0% or 40% correlation.

For recoveries, all issuers and seniorities are grouped together. For each combination, one of 11 ranges is selected from the PMF (i.e., 0–10% recovery, …, 90–100% recovery, 100+% recovery) and the average recovery from that range is assigned. This is the same logic as the ACLI/MA Bond Model, except the PMFs and average recovery rates differ between senior and non-senior loans.

Another model simplification is that the senior and non-senior recoveries are sampled independently, even if they share the same issuer. It is expected that the senior loan's recovery rate should always be at least as high as the subordinated tranche recovery rate. When sampling independently, some subordinated tranches will end up with higher recovery rates than the issuer's senior loans.

The Academy chose not to explicitly address this because S&P joint recovery rates were not available. A proxy solution, such as sampling the senior tranche's recovery first and then sampling the subordinated tranches from a truncated distribution, will artificially suppress the average recovery rates. For example, if the senior tranche recovers more than 100% of principal, it is more likely that the subordinated tranche will also fully recover, but the magnitude of this increased likelihood cannot be determined without a joint PMF distribution. Hence, the Academy determined that independent sampling, while theoretically unintuitive, introduces the least additional bias and modeling error.

After the simulation function is run, the resulting data table contains every pair of issuer and seniority with one column indicating the time of default in years (-1 if no default is sampled), another column indicating the recovery as a proportion of par and a final column indicating the simulation number (1 through 10,000).

5.1.1.4 Reinvestment Modeling

While the losses on *initial* or *original* collateral follow the simulated output, the reinvestment of recovered principal and interest is an important component of a CLO's ultimate risk profile and is not a trivial modeling exercise. The Academy considered five reinvestment methodologies:

1. **Use parametric average loss rates**

   In this approach, all reinvested asset losses are modeled using the parametric average default and recovery rate assumptions.

   Pros: This method is the simplest and is the easiest to replicate, as it does not rely on random sampling.

   Cons: This method creates a disconnect between the original collateral simulated losses and the reinvested asset losses. The method will understate the tail risk. A tail risk scenario will have above-average losses in both the original collateral and in the reinvested assets. By assigning average losses to the reinvested assets, the tail risk from reinvested assets is ignored.

2. **Stochastically simulate reinvestment losses**

This method would extend the simulation model to the reinvested assets. Within each simulation, the recovered balance would be calculated for each year. New loans would be added to the next year's loss simulation and would be affected by the same systematic risk factor in the copula. Additionally, the time-since-rating would differ between original collateral and reinvested collateral (e.g., in year-3, original collateral is 3 years from rating but investments on year-2 recovered principal will be 1 year from rating). This method would also account for principal recovered on reinvested assets that also default. The losses would then be averaged into vectors that can be read by CDOnet.

Pros: This method is the most accurate because it accounts for the fact that reinvested assets are subject to the same systematic risks as the original collateral (which can compound tail risk) and accounts for the fact that reinvested assets will have time-since-rating offset with the original collateral.

Cons: This method is too convoluted and computationally expensive. The simpler methods already have extensive run time. This model also creates false precision because it requires assumptions about issuer diversification without knowing the behavior of the actual CLO managers. If the reinvested assets are only new issues (i.e., loans that do not already exist in the collateral's loan universe), this will over-diversify. If the reinvested assets are all issuers contained in the original collateral, it will under-diversify.

3. **Average simulated loss rates, starting at time of reinvestment**

This method takes the simulated defaults and averages them by year and rating. The simulated recoveries are averaged by year and seniority. The simulated amount available for reinvestment would follow these average default and recovery rates starting at *time of reinvestment.* For example, suppose some loans default in year-2 and are reinvested in B1 senior loans in year-3. If the original collateral rated B1 defaulted at a rate of 5% in year-1 and senior loans recovered 40%, then the reinvested B1 senior loans would have a 5% default rate in year-3 (i.e., year-1 from the time of reinvestment) with a 40% recovery rate.

Pros: By using the loss rates from the simulations, it reasonably captures tail risk in the reinvestments. By starting the rates from the time of reinvestment, it properly accounts for rating migration. Marginal default rates generally increase in the second year (over the first) and thereafter decrease. Reinvested assets could be riskier because they have yet to experience positive rating migration. By aligning the time-since-rating, this method accounts for that misalignment.

Cons: This method creates a misalignment in the systematic risk factors between the original collateral and the reinvested assets. For example, if a large systematic risk is sampled in year-1, then the original collateral will have higher default rates in year-1. This means that all reinvested assets will be assigned this large systematic risk in their first year of issuance, even if the original collateral has less severe systematic risks in all subsequent years. In this case, the year-1 stress scenario is being overstated within the reinvested assets and overstates the risk. On the flip side, if the most severe systematic risk occurs in year-6 for the original collateral, then the reinvested assets may never reach the stress scenario, even if reinvested assets are live in year-6. For example, a new asset purchased in year-5 will in practice experience the year-6 stress scenario, but in this model, the simulation will end before the reinvested asset gets to its own sixth year. This case understates the risk of the CLOs.

4. **Average simulated loss rates, starting at time 0**

   This method is identical to the prior method, except the default and recovery vectors are keyed to time 0 rather than the time of reinvestment. For example, if the original collateral has a stress scenario in year-3, then all reinvested assets in force during year-3 are assigned the same default rate and same recovery rate as the original collateral. In the prior method, the reinvested assets would be assigned the year-3 default/recovery rate after being in force for three years.

   Pros: Like the prior method, this is computationally simpler than stochastically modeling the reinvestments. Furthermore, it addresses the con in the prior solution by aligning the systematic risk factors. If a year has a severe systematic risk, that systematic risk affects the reinvested assets as well, rather than being misaligned. This should better reflect the tail risk of a CLO since a CLO is under the most stress when underlying loans simultaneously default.

   Cons: This method has a slight mismatch in the ratings due to rating migration. If recovered principal is reinvested into a B1 asset in year-3, the default rates are derived from loans that were rated B1 at the start of year-1, not at year-3. Some of those loans may have experienced rating migration so the year-3 default rates do not reflect a newly rated B1 loan.

5. **Average simulated loss rates, starting at time 0, expected ratings**

   This method is identical to the prior but would estimate an expected credit rating at the time of reinvestment. Maximum-likelihood ratings for each issuer and each year are derived using the original rating, the time of default, and a rating transition matrix. The average default rates for each year would be derived from the expected ratings rather than the original ratings, thus accounting for the rating migration issue noted in the prior method.

   Pros: This method improves over the prior two methods by aligning both the ratings and systematic risk factors.

   Cons: This method introduces new modeling assumptions, as it requires a transition matrix. It also depends on how maximum likelihood is calculated. This can be convoluted in implementation and lacking in transparency. Comparing this method to the prior, it is unclear whether it is more accurate at a statistically significant level, or if it is distorted by added model assumptions.

From the above five methods, the Academy chose Method 4. Method 1 was not seriously considered because it fails to account for tail risk altogether. Method 2 was briefly considered but ruled out and never tested due to computational limitations. Method 3 was chosen initially to align credit quality. However, after running the six sample deals, it became clear that the systematic error component was the primary driver of tail risk as evidenced by the ACLI/MA Bond Model's sensitivity to the correlation parameter. Accordingly, Method 4 was chosen to align systematic risk factors. Because the reinvestment horizon is in general only 2–3 years, rating migration is a relatively minor problem. Finally, Method 5 was briefly discussed and proposed as a solution to the ratings mismatch, but it was never implemented due to skepticism of false precision and adding more model assumptions.

While collateral losses are simulated across all deals, each CLO's matured balance and recovered balance must be modeled individually per deal. Ideally, the Collateral Model would read in the reinvestment end date for each deal as well as the parameters for reinvestment (e.g., the distribution of credit quality, distribution of seniority for new purchases and average time to maturity). However, due to operational complexity and to reduce model risk, a single set of reinvestment assumptions was used in the Collateral

Model across all deals:

- **Reinvestment horizon:** 2.5 years
- **Credit distribution:** 30% B1, 30% B2 and 40% B3
- **Seniority distribution:** 92.5% senior, 7.5% non-senior
- **Reinvested asset maturity:** Greater than 10 years

This creates a discrepancy between the Collateral Model (single set of reinvestment assumptions across all deals) and the Cash Flow Model (individual CLO deal-specific assumptions are used). If the model is enhanced in future iterations, the code may be adjusted to soft code these assumptions at the deal level along with the CDOnet reinvestment assumptions. That said, the Academy found that the assumptions were reasonable for running the sample deals.

5.1.1.5 Selecting Tail Scenarios

To achieve the highest precision possible in modeling, all 10,000 simulations of collateral cash flows would be passed through CDOnet. But due to run-time constraints, the Academy was only able to run CDOnet a limited number of times. The Academy chose 17 tail scenarios and a VaR70 scenario to pass through CDOnet (see Appendix C). Each tail scenario represents VaR for a given percentile. The percentiles are increasingly granular towards the right side of the loss tail. The 17 sets of C-1 Factors derived from the CDOnet results are subsequently averaged together using the Midpoint Riemann Sum method to estimate CTE90 (see Appendix C).

The task of choosing the appropriate simulation to represent VaR at a given percentile is not trivial. The goal is to approximate CDOnet's output and reasonably rank-order the simulations.

When processing the original collateral by deal, the time-to-default is pulled for each line item based on its issuer. If the default occurs at the loan's time-to-maturity or before, then a default is assigned as well as the simulated recovery rate. Otherwise, the loan is assumed to have fully matured (even if the issuer does default at a later point in the 10-year window).

In accordance with reinvestment Method 4, the total balance (across all loans) of defaulted issuers is summed, grouped by rating and default year and is divided by the initial balance per rating. This produces default vectors for reinvestment by rating. Grouping by seniority and year, the balance recovered on defaulted issuers is recorded as a proportion of total defaulted balance. This produces recovery vectors for reinvestment by lien.

Before the sixth month of year-3 (i.e., by the end of the 2.5-year reinvestment period), all matured balance and all balance recovered from defaults is summed together and constitutes the reinvested balance. The reinvested balance times the probability of default times the loss-given-default (equal to 1 − recovery rate) is recorded as a loss in a given month. Recovered balance—defined as the reinvested balance times default rate times recovery rate—is added back to the reinvested balance for the next period. At the sixth month of year-3 and thereafter, recovered balance is strictly removed from the reinvestment pool. This procedure generates a vector of losses on reinvestments by month.

The vector of losses from the original collateral and losses from the reinvested amounts are summed together. The total losses are discounted to time 0. A 3.47% (pre-tax) discount rate is used to match the bond model assumption. Losses are assumed to occur mid-month, on average. Thus, a loss that occurs during month-1 is discounted by $(1 + 3.47\%)^{1/24}$. The sum of all discounted losses is recorded as the simulation's present value.

The simulations are rank-ordered by their estimated present value of loss and the 18 target percentiles are selected. For each one, the period of default (year, month) and the recovery rate given default are saved

along with the default and recovery vectors for reinvestment (using Method 4 logic described above).

5.1.2 Step 2—CDOnet Cash Flow Projection Model

Cash flow modeling is performed using CDOnet, the structured credit cash flow engine provided by Moody's Analytics (Cash Flow Model). The default rate and recovery rate vectors from the Collateral Model are input into the Cash Flow Model. The Cash Flow Model also inputs parameters for each CLO deal and outputs cash flows by tranche.

CDOnet accepts approximately 100 distinct inputs per run. Of these, 22 are identified as modeler assumptions (as opposed to deal-specific structural parameters extracted directly from deal documents). See Appendix O for the full list of assumptions. The remaining inputs are CLO deal parameters, i.e., fixed facts such as tranche balances, payment dates, coupon rates, attachment/detachment points and contractual structural features. These inputs are populated from deal-level data and are not subject to discretionary modeling choices. The 22 assumption inputs, particularly those designated as material, are the primary focus of this section.

As a general principle, except where explicitly noted, all CDOnet parameters are set in accordance with the NAIC SSG CLO modeling methodology documented on the SSG CLO webpage. This provides an established, publicly available baseline that ensures consistency with regulatory practice and reduces the risk of idiosyncratic or unsupported assumption choices. The Academy's deviations from SSG are intentional and each has a documented rationale grounded in the C-1 RBC framework.

5.1.2.1 Modeling Methodology

The Academy identified six high-level modeling topics for deliberation, each of which directly shapes one or more CDOnet inputs. These categories serve as the organizing framework for the assumption set:

Category	Brief Description
Discount Curve	The reference curve used for valuing cash flows
Credit Spreads	Market spreads applied to the discount margin
Default Rates	Default assumptions applied to collateral
Recovery Rates	Post-default recovery assumptions
Prepayment Rates	Voluntary prepayment behavior of collateral
Reinvestment	Assumptions governing reinvestment of principal proceeds during the CLO's reinvestment period

A seventh topic—whether to capture seasoning of individual CLO deals—was identified as an open question by the Academy. While explicit modeling within CDOnet was not incorporated, seasoning of individual CLO deals was indirectly reflected through the data and parameters used.

The following subsections detail the most discussed of the 22 identified assumptions, with special emphasis on those flagged as material by the Academy. For each, the SSG baseline is noted where applicable, and the Academy's recommendation and rationale are described.

5.1.2.2 Default Vectors and Scenario Selection

Academy recommendation: Analyze 17 tail scenarios (and one benchmark 70th percentile scenario) selected from the full 10,000-scenario output of the Collateral Model, as described in the previous section. Defaults and recoveries are stochastically simulated and configured to data that can be read by CDOnet.

SSG approach: SSG uses 10 weighted default and recovery scenarios, selected and weighted to minimize the difference between the CLO-level C-1 Factor and the underlying collateral-level C-1 Factor (i.e., enforcing CLO/collateral C-1 equivalence).

Rationale for departure: The Academy's approach does not enforce CLO/collateral C-1 equivalence but

emphasizes modeling consistency where appropriate. The goal of the C-1 CLO factor is to accurately capture the actual credit loss distribution at the CLO tranche level, not to tie it arithmetically to a collateral-level measure. Using 17 scenarios drawn from the full stochastic tail provides a more comprehensive and direct representation of the loss distribution relevant to each tranche. This approach has the further benefit of creating continuity between the ACLI/MA Bond Model and the modeling of CLO collateral.

5.1.2.3 Collateral Prepayment Rate (CPR) and Reinvestment Price

Academy recommendation: No prepayment (CPR = 0%) and reinvestment at par.

SSG approach: No prepayment and reinvestment at par.

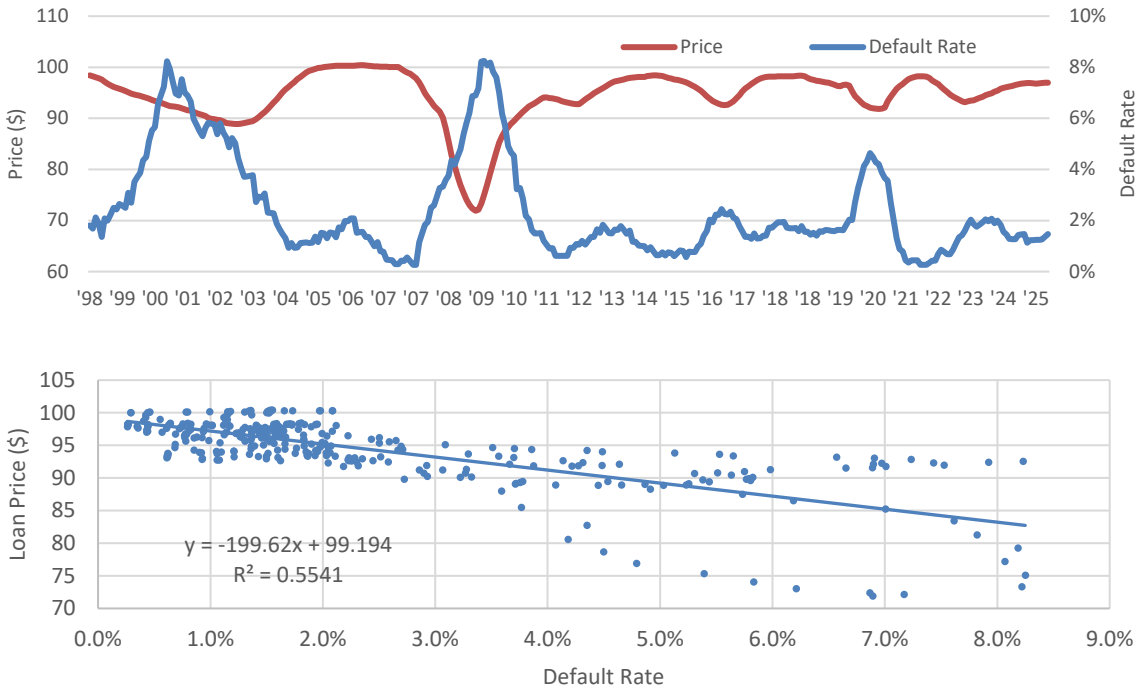
Rationale: This approach is consistent with major rating agency CLO stress methodologies (Moody's, S&P, Fitch), which generally assume no explicit voluntary prepayment under stress. Although eliminating voluntary prepayment does not always result in a more conservative modeled outcome, when combined with reinvestment at par, it increases default exposure and produces more conservative outcomes.

The assumption of reinvestment at par is one of the most frequently discussed assumptions in the C-1 Subcommittee. While reinvesting at par during a stress scenario (where secondary market prices would be distressed) may appear to layer conservatism on top of conservatism, the Academy concluded it is appropriate for consistency with the ACLI/MA Bond Model. In the bond C-1 framework, a five-year bond modeled at the 96th percentile stress scenario is subsequently reinvested and that reinvestment also occurs at par, persisting in the same stress environment. Maintaining the same convention for CLO collateral reinvestment ensures methodological coherence across the C-1 framework. Importantly, the C-1 Subcommittee noted that care must be taken to ensure the 10-year stress horizon is not exceeded as a result of reinvestment mechanics.

A counterargument considered is that the bond model's assumption of reinvestment at par serves to estimate the amount of surplus an insurer will need to replenish reserves. By contrast, CLOs are actively managed and the cost of reinvestment is borne primarily by the equity tranche. While a default directly affects the insurer's surplus in the bond model, a loan default does *not necessarily* result in a default on the CLO debt. Therefore, a divergence from the bond model could plausibly be justified.

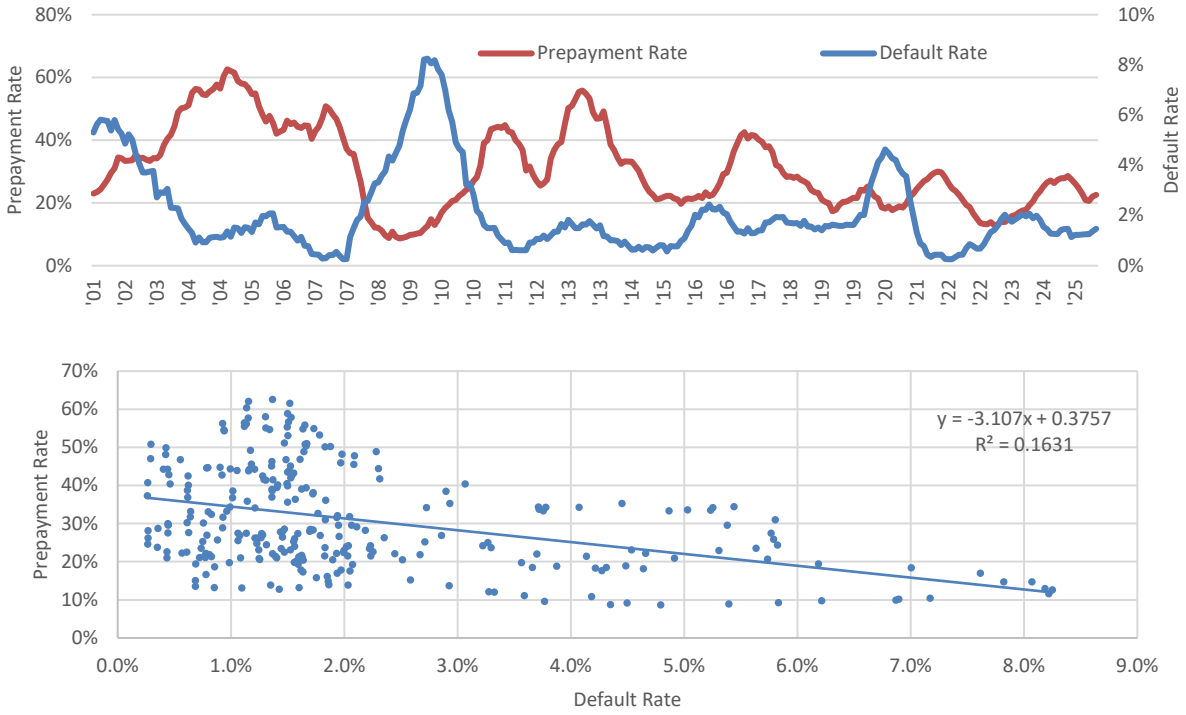
Furthermore, the Academy considers the correlation between default rates, prepayments, and reinvestment prices. When defaults increase, the price of loans is discounted, so reinvesting during a high default period could be done at a discount to par.

Figure 4 - Leveraged Loan Index Default Rate vs. Price Rolling 12-months



A similar trend holds with prepayments. When defaults are more common, the rate of prepayment declines.

Figure 5 - Leveraged Loan Index Default Rate vs. Prepayment Rate Rolling 12-months



As recorded in Appendix K, Sensitivities 6 and 7, the Academy considered tail risk averages (based on high default rate periods) for the prepayment rate and reinvestment price. The Academy found that the resulting C-1 Factors are highly sensitive to these assumptions.

The assumptions were chosen based on the simplicity of implementation and judgment, erring on the conservative end. With further research, these assumptions could be revised with more sophisticated modeling.

5.1.2.4 Recovery Lag

Academy recommendation: Immediate recovery; no lag between default event and recovery of proceeds.

SSG approach: 6-month lag between default and recovery.

Rationale: The Academy's choice of immediate recovery is consistent with S&P recovery data conventions, which measure ultimate recovery without applying a time-value penalty for resolution timing. Because the C-1 Factor Model already discounts all cash flows to present value, embedding an additional lag assumption would double-count the time-cost of default resolution. This is a deliberate departure from SSG practice.

5.1.2.5 Structural Trigger Assumptions (OC/IC Tests)

SSG approach and Academy recommendation: Overcollateralization (OC) and Interest Coverage (IC) tests are modeled per deal documentation, with the standard waterfall mechanics active. These triggers are deal parameters in the strict sense—their thresholds come from deal documents—but the behavioral assumption (i.e., that they function as written and are not waived or modified) is an analytical choice.

Rationale: Allowing OC/IC triggers to redirect cash flows (e.g., de-levering the senior tranches at the expense of junior tranches) is essential to accurately modeling CLO structural protection under stress. Disabling these mechanisms would materially understate tranche-level credit enhancement.

5.1.2.6 Fees and Expenses

SSG approach and Academy recommendation: Deal-specific fees (management fees, trustee fees, administrative fees) are input per deal documents. Where deal-specific data is unavailable, standard market fee schedules are applied. These are modeled as senior waterfall items and are deducted prior to interest payments to rated tranches.

5.1.2.7 Other Assumptions

The remaining assumptions include:

- LIBOR/SOFR transition treatment: applicable to legacy deals with LIBOR-referenced collateral; transition handled per Alternative Reference Rates Committee (ARRC) conventions embedded in CDOnet.
- Floor and cap assumptions: modeled per deal documents where interest rate floors/caps exist on collateral or liabilities.
- Optional redemption and refinancing: assumed not to occur during the stress horizon (conservative; consistent with no-prepayment rationale).
- Workout and restructuring assumptions: distressed collateral is modeled as defaulted with the prescribed recovery rate; no partial workout credit is given.
- Collateral diversity and concentration limits: deal-specific; modeled per portfolio data as of the modeling date.

- Currency/FX assumptions: U.S. dollar denominated; FX assumptions not applicable to the primary model run.
- Manager quality: Not explicitly modeled as a qualitative overlay; all CLO managers are treated equivalently within CDOnet.

5.1.3 Step 3—C-1 Deal-Level CLO Factor Model

The output files from CDOnet summarize the projected cash flows with the following fields:

- **DEAL_KEY**: Unique system identifier for the CLO deal. Links tranche-level cash flows back to the deal-level collateral pool and structural parameters in CDOnet.
- **TR_KEY**: Unique system identifier for the individual tranche within the deal. Used to join tranche-level cash flows to tranche structural attributes (attachment point, detachment point, rating, etc.).
- **TR_NAME**: Human-readable tranche label as defined in the CLO deal documentation (e.g., "ER2" denotes the second equity/residual tranche). Used for reporting and cross-referencing against the deal term sheet.
- **SCEN**: Scenario index corresponding to one of the 18 percentile scenarios. Scenario 1 corresponds to the 90th percentile, Scenario 17 corresponds to the 99.99th percentile and Scenario 20[19] corresponds to the 70th percentile, for reference.
- **PERIOD**: Sequential monthly period index beginning at 0. Period 0 represents the initial state; subsequent periods represent monthly payment dates through deal maturity or full paydown.
- **PAY_DATE**: Calendar date of the payment period. CDOnet projects cash flows on actual payment dates, following the CLO's contractual payment schedule (typically monthly or quarterly distributions to noteholders).
- **BALANCE**: Outstanding principal balance of the tranche at the end of the period. In this scenario the balance grows during the reinvestment period as new loans are added to the collateral pool, then drops to zero when the tranche is fully written off due to losses.
- **INTEREST**: Cash interest actually paid to the tranche in the period.
- **PRIN**: Cash principal returned to the tranche in the period.
- **LOSSES**: Principal losses allocated to the tranche in the period. Zero in all periods except the final period, where the full outstanding balance plus accumulated deferred amounts are written off, representing complete tranche loss at deal wind-down under this extreme scenario.
- **INT_DUE**: Interest accrued and contractually due to the tranche in the period but not yet paid.
- **INT_DEFERRED**: Cumulative unpaid (deferred) interest balance outstanding as of the period end. Missed CLO tranche payments are recorded as deferrals rather than defaults, consistent with the Academy's C-1 methodology, which distinguishes between tranche payment deferral and outright default.
- **ARREARS**: Principal arrears balance: principal that was contractually due but not paid in the

[19] Scenario numbers were arbitrarily assigned by the Academy for record-keeping purposes.

period.

- **INT_ARREARS**: Interest arrears balance: a sub-component of deferred interest tracking amounts that have aged beyond a specified grace period or that are in formal arrears status per the deal indenture.

- **TR_COUPON**: The tranche coupon rate applicable in the period, expressed as an annualized percentage. The rate is presented as an annualized nominal rate.

5.1.3.1 Debt C-1 Calculations

A C-1 Factor is intended to represent the maximum present value of loss beyond the risk premium as a proportion of current balance.

Within statutory accounting, an impairment may be taken when there is an expectation of loss. The Academy chooses to assume, for the sake of modeling, that the reporting insurer has perfect foreknowledge. First, this means that the C-1 Factor is always equal to 0 if the final losses are 0; if a payment is missed but ultimately paid, the Academy assumes that no impairment was taken. The code defaults the C-1 to 0 whenever the final loss is 0 to avoid non-zero C-1 from rounding errors. Second, this means that an impairment is taken immediately when the CLO first misses a payment (on either interest or principal) and ends with a non-zero loss.

In the ACLI/MA Bond Model, the risk premium is assigned by rating and is estimated as half a standard deviation above the mean present value of losses. For a standard normal distribution, the 69.15th percentile is one-half of a standard deviation above the mean. Therefore, the Academy considers the 70th percentile as a benchmark for risk premium. Unfortunately, the Raw C-1 Factors at the 70th percentile are erratic and do not increase alongside decreases in credit quality (see Appendix E). Because of the instability of the 70th percentile Raw C-1 Factors and computational constraints, the Academy defers to the existing risk premia numbers used in the ACLI/MA Bond Model.

Also consistent with the ACLI/MA Bond Model, the discount rate is 3.47%, the tax rate is 21% and the tax loss recovery rate is 80%. The adjusted tax rate is then $21\% \times 80\% = 16.8\%$, identical to the ACLI/MA Bond Model. Additionally, the Academy assumes an accumulation rate equal to the discount rate, 3.47%.

With these assumptions, the C-1 Factors are calculated. Appendix D Illustrative CLO Debt Cash Flows to Raw C-1 Factors provides an illustrative example of the calculations. The added fields are as follows:

- **TOTAL_CF:** the sum of INTEREST and PRIN in each period. This represents the total cash received by the investor from the tranche in that period, both the coupon payment and any principal returned.

- **INNER_LOOP_PV:** for each period i, the present value of all future cash flows (TOTAL_CF) from periods i+1 onward, discounted back to period i using the tranche's own coupon rate (TR_COUPON, converted to a monthly rate) as the discount rate. Specifically, for each future period j > i, the cash flow TOTAL_CF[j] is discounted by $(1 + \text{TR_COUPON}[j])^{j-i}$, and all such discounted values are summed. The upper triangular matrix construction enforces that only forward-looking cash flows contribute. This represents the intrinsic economic value of the tranche at each point in time as seen through the lens of its own promised yield. This is the benchmark against which the carrying book value is compared to determine whether an impairment has occurred.

- **PRE_IMPAIRMENT_BV:** the carrying book value of the tranche at the start of each period, before any impairment write-down is applied. In the first period it is initialized to

BALANCE[1] (par value). In each subsequent period r it is rolled forward as: PRE[r] = POST[r−1] × (1 + TR_COUPON[r]) − TOTAL_CF[r]. This is a standard amortized cost carrying value: the prior post-impairment book value accretes at the coupon rate and is reduced by any cash received. It represents what the investor's balance sheet would show before considering whether a further write-down is warranted in the current period.

- **IMPAIRMENT_FLAG:** a binary indicator (0 or 1) that is set to 1 in the first period where two conditions are simultaneously met: (1) the tranche has a non-zero deferred interest balance (INT_DEFERRED > 0) or unpaid principal arrears (ARREARS > 0), signaling that the tranche is not paying in full; and (2) INNER_LOOP_PV is less than PRE_IMPAIRMENT_BV, meaning the present value of remaining cash flows is insufficient to recover the current book value. Once triggered, the flag is permanently latched at 1 for all subsequent periods. This reflects the accounting principle that once an asset is impaired, it remains on an impaired basis even if conditions temporarily improve.

- **IMPAIRMENT:** the write-down amount applied to the book value in each period. It is computed as max(0, PRE_IMPAIRMENT_BV − INNER_LOOP_PV) × IMPAIRMENT_FLAG. When the flag is active, this is the excess of book value over the present value of remaining cash flows, i.e., the amount by which the asset is "underwater." When the flag is zero, the impairment is forced to zero regardless of the present value gap.

- **POST_IMPAIRMENT_BV:** the carrying book value after applying the period's impairment write-down: POST[r] = PRE[r] − IMPAIRMENT[r]. This is the balance sheet value carried forward into the next period's PRE_IMPAIRMENT_BV calculation. Once impairment is recognized and the book value is written down to INNER_LOOP_PV, subsequent accrual occurs from this lower base, preventing double-counting of losses already recognized.

- **RISK_PREMIUM:** a carrying-cost charge applied each period equal to −POST_IMPAIRMENT_BV × (risk premium / 12), where the risk premium is the premium from the ACLI/MA Bond Model for the given rating. It is set to zero in the first period. The risk premium represents the incremental return above the risk-free rate that a rational investor requires to hold an impaired or at-risk tranche.

- **PV_ACCUM_DEFICIENCY:** the pre-tax accumulated present value of all capital deficiency events—impairments and risk premium charges—recognized through each period, measured in present value terms as of period 0. It is computed in three steps: (1) each period's (RISK_PREMIUM + IMPAIRMENT) is scaled by a monthly accumulation factor k = (1 + accumRate / 12) to reflect reinvestment of recognized losses at the accumulation rate; (2) a running cumulative sum of these scaled values is taken and multiplied by k^t to bring the balance to the end of period t; and (3) the accumulated balance is discounted back to period 0 by dividing by (1 + discountRate / 12)^PERIOD. The first period is set to zero by construction. The maximum of this series across all periods forms the numerator of the pre-tax C-1 Factor. That is, it represents the worst-case present value of the capital a life insurer would need to hold to absorb the losses generated in this stress scenario.

- **TAX_BASIS:** the investor's tax basis in the tranche in each period, defined as (BALANCE + ARREARS) when POST_IMPAIRMENT_BV is positive, and zero otherwise. This captures the original cost basis—par plus any accrued but unpaid principal—that the investor is entitled to use for tax loss purposes. It goes to zero when the tranche has been fully written off (POST_IMPAIRMENT_BV = 0), reflecting that there is no remaining basis to deduct once the position is extinguished.

- **UNREALIZED_TAX_LOSS:** the difference between TAX_BASIS and POST_IMPAIRMENT_BV: UNREALIZED_TAX_LOSS = TAX_BASIS − POST_IMPAIRMENT_BV. This measures the gap between what the investor paid (tax basis) and what the tranche is currently worth on the books. The embedded loss has not yet been realized for tax purposes. It drives the deferred tax asset calculation in the following column: an unrealized tax loss creates a future tax benefit that partially offsets the economic loss.

- **REALIZED_TAX_LOSS:** the tax loss realized in each period, multiplied by the adjusted tax rate to convert to a tax cash flow benefit. In the first period it equals −min(TAX_BASIS, LOSSES) × adjTaxRate, capturing the tax benefit from principal losses allocated to the tranche at inception. In subsequent periods it equals (−min(prev_basis, LOSSES) − prev_basis × 1[first impairment period with full write-off]) × adjTaxRate, capturing both ongoing principal losses and the full write-off of the remaining tax basis when the tranche transitions from unimpaired to fully impaired in a single period. The tax benefit from realized losses reduces the effective after-tax cost of credit losses to the insurer.

- **DTA_CHANGE:** the change in the deferred tax asset from one period to the next, computed as (UNREALIZED_TAX_LOSS[r−1] − UNREALIZED_TAX_LOSS[r]) × adjTaxRate, with the first period set to zero. An increase in the unrealized tax loss—meaning the gap between tax basis and book value is growing—creates a positive deferred tax asset (DTA) representing a future tax benefit that reduces the insurer's net capital requirement. A shrinking unrealized loss, for example after a cash interest payment, reverses the deferred tax asset. Including deferred tax asset changes in the accumulated deficiency calculation converts the pre-tax C-1 Factor into a true after-tax measure of capital need.

- **PV_ACCUM_DEFICIENCY_TAX_ADJ:** the after-tax analog of PV_ACCUM_DEFICIENCY. It follows the identical accumulation and discounting structure but uses post-tax rates (postTaxAccumRate, postTaxDiscountRate) and includes REALIZED_TAX_LOSS and DTA_CHANGE alongside RISK_PREMIUM and IMPAIRMENT in the deficiency stream, so that each period's contribution is (RISK_PREMIUM + IMPAIRMENT + REALIZED_TAX_LOSS + DTA_CHANGE).

The maximum of the PV_ACCUM_DEFICIENCY series across all periods, divided by the initial BALANCE, is the pre-tax C-1 Factor (PV_ACCUM_DEFICIENCY_TAX_ADJ produces the post-tax C-1 Factor). The final Raw C-1 Factor is the post-tax factor.

Finally, a weighted average of the 17 tail scenarios is calculated for each CLO debt tranche, estimating each CTE90. The weights are derived from the Midpoint Riemann Sum method (see Appendix C, Scenario Weights).

5.1.3.2 Equity C-1 Calculations

Under Statutory Accounting Principles (SAP), there are two ways insurers can account for residual tranche equity: allowable earned yield (AEY) and practical expedient. The Academy calculates a separate set of C-1 Factors for each of the two accounting methodologies.

AEY requires the insurer to estimate the book yield of the residual tranche as the internal rate of return (IRR) that equates best-estimate projected cash flows with the purchase price. The book yield times outstanding book value constitutes the "allowable" income. Any income above the "allowable" income reduces or pays down book value. Any time the residual tranche fails to pay out the book yield, a shortfall is recorded and it can be made up by future payments. Once the book value is reduced to $0, all payments are recorded as income.

If a residual tranche, whose book value is $100 and book yield is 20%, receives $30 in a year, the first $20 is income and the remaining $10 ($30 − $20) is paid down book value. This means the book value is reduced from $100 to $90. In the next year, the allowable yield is $18, i.e., 20% of $90, which means that an additional $30 is recorded as $18 of income and $12 of book value. By contrast, if the residual tranche pays only $10 in the first year, a $10 shortfall is recorded and $30 is owed the next year (due to the additional $20 of allowed income in the second year). If the residual tranche pays $30 in the next year, the shortfall is brought back down to 0. If it exceeds $30, then the amount in excess of $30 is paid down as book value.

Practical expedient accounting is a special case of AEY where the book yield is set equal to 0%. This means that no income is recorded until the book value is fully reduced to $0.

In Table 4, a simple illustration is presented where the residual tranche has a balance of $100. Note that when there is an outstanding shortfall, the amount recorded as income can exceed that year's AEY (until the shortfall is closed). Under practical expedient there is no concept of shortfall, and income is only recorded after the book value is brought down to $0.

The total income earned under AEY sums to $89 while the income sums to only $49 under practical expedient. This is not an accounting error; it is explained by the outstanding $40 of book value under AEY. Any outstanding book value is realized as a loss when the position closes. In this example, the realized IRR is 13%, well below the 20% book yield, which is why a loss is recorded.

Table 4 - Residual Tranche Accounting Illustration

			Allowable Earned Yield (20% IRR)				*Practical Expedient*		
Period	*Balance*	*Interest*	*Book Value*	*Allowed Yield*	*Income*	*Shortfall*	*Book Value*	*Income*	*Shortfall*
0	$100		$100				$100		
1	$100	$30	$90	$20	$20	$0	$70	$0	$0
2	$100	$10	$90	$18	$10	$8	$60	$0	$0
3	$100	$20	$90	$18	$20	$6	$40	$0	$0
4	$100	$39	$75	$18	$24	$0	$1	$0	$0
5	$100	$50	$40	$15	$15	$0	$0	$49	$0

Any change to a residual tranche's book value will result in a 1-to-1 change to its owner's Total Adjusted Capital (TAC), which is the numerator of the RBC ratio. Because practical expedient's book value falls faster than AEY's, it contributes less to TAC. It also requires a more severe loss event to cause a loss on book value. Additionally, because the Academy assumes equity does not back liabilities, statutory income generated by residual tranches is assumed to increase surplus 1-to-1. Such income can offset later losses, since C-1 estimates only *net* surplus required to cover losses.

When estimating the book yields for AEY, the Academy pulls the historical balance, principal (i.e., contributions to balance[20]) and interest paid by the residual tranche. The Academy also runs a baseline simulation through CDOnet to produce future projected cash flows. In this baseline run, the default rates by year and rating and the recovery rates by lien are set equal to the Collateral Model parameters (i.e., the average). The resulting projected cash flows are concatenated with the historical cash flows and a simple cash flow IRR is calculated.

[20] When a CLO reset occurs, the Academy assumes that the observed increase in principal balance results from a corresponding capital contribution of the same amount. However, this is not necessarily the case and may result in imprecise estimates of starting book values.

Appendix F shows 42.55% of residual tranches have an IRR ≤ 0%. Among the securities that have non-zero IRRs, the average IRR is only 9.43% with a median of 7.06%. The total average IRR is 5.42% and the total median is 2.29%. This is well below typical IRR projections for residual tranches, and it suggests that the Collateral Model parameters (default rates and recovery rates) may be unrealistically conservative.[21]

The model's conservatism is exacerbated by the fact that the IRRs should be skewed up by survivorship bias. The Academy has already filtered the universe to securities that are outstanding on 12/31/24; residual tranches of CLOs that defaulted before 12/31/24 are already excluded. Rather than going back to the start date of each CLO and running the projections from then, the Academy assumes that the insurer precisely estimated the cash flows that occurred before 12/31/24. This carries the implicit assumption that the insurer correctly predicted the survivorship, which will skew up any IRR calculation. This bias is borne out in the data. Among CLOs with no historical cash flows (before 12/31/24), the mean IRR is only 2.50% and median is 0.00% (well below the mean and median IRRs for seasoned residual tranches).

Nevertheless, to retain internal consistency, the Academy uses the baseline IRRs as the book yield when estimating book values under allowable earned yield.

For each security and each of the simulations from CDOnet, the Academy concatenates the projected cash flows with the historical cash flows. The Academy assumes that the insurer bought the residual tranche at issue and set the initial book value equal to the initial balance. For the full time series (history and projected), the calculated fields are as follows:

- **TOTAL_CF:** the sum of INTEREST and PRIN in each period. This represents the total cash received by the investor from the tranche in that period. PRIN is 0 in the future projections but can be negative in the historical cash flows when additional principal was contributed to the tranche by the investor.

- **MAX_AEY:** Prior book value (balance at the start) times the book yield (allowable earned yield). This is the maximum amount of additional income that can be recorded.

- **SHORT_FALL:** Calculated as min(INTEREST − MAX_AEY + prior SHORT_FALL, 0), this represents the cumulative allowable income missed. If the interest is large enough to cover new allowable earned yield and the prior shortfall, the shortfall is brought to 0. When a shortfall exists, the field SHORT_FALL is negative.

- **PAID_BV:** Calculated as min(prior BV, max(INTEREST − MAX_AEY + prior SHORT_FALL, 0)), this represents the leftover interest that goes towards paying down book value. If the interest exceeds AEY and shortfall, the interest pays down book value (and cannot exceed prior STAT_BV, since BV does not go below 0).

- **PAID_OFF_BV_INCOME:** Calculated as max(INTEREST − MAX_AEY + prior SHORT_FALL − PAID_BV, 0), this represents the amount of interest that gets calculated as income after STAT_BV goes to 0. Once STAT_BV is 0, all interest is income.

- **STAT_INCOME_PRE_TAX:** This is the total statutory income. It is calculated as min(INTEREST, MAX_AEY) + max(SHORT_FALL − prior SHORT_FALL) + PAID_OFF_BV_INCOME. If the interest is below the MAX_AEY, then all interest is statutory

[21] Because the residual tranche has a higher risk of loss than any of the debt tranches, investors would only buy the residual tranche if they expect it to generate a higher return than what they expect on the debt tranches. Yet these IRRs of 5.42% or 2.29% are well below the yields paid by debt tranches. When a model disagrees with market pricing, a prudent modeler defers to the market and looks for potential flaws in the model.

income. If it exceeds the AEY, the AEY goes to income as well as any recuperated shortfall. If the book value falls to 0, the statutory income is realized through PAID_OFF_BV_INCOME.

- **TAX:** −21% × INTEREST. All interest is taxed at the standard rate. The sign is flipped to negative because it constitutes a reduction in statutory income.

- **STAT_INCOME_POST_TAX:** STAT_INCOME_PRE_TAX + TAX.

- **STAT_BV:** Calculated as max(prior STAT_BV − PAID_BV − PRIN, 0), the book value is reduced by interest in excess of the AEY (and recuperated shortfall) and is adjusted by principal payments (the principal payments are only applicable to historical cash flows).

- **REALIZED_LOSS_BV:** Equal to −STAT_BV in the final period and 0 everywhere else, this is the remaining book value that is recorded as an accounting loss.

- **REALIZED_LOSS_BALANCE:** Equal to −BALANCE in the final period and 0 everywhere else, this is the remaining balance that is recorded as a loss for tax purposes.

- **DTA:** Equal to 0 in the last period, the DTA is everywhere else 21% × (BALANCE − STAT_BV). When the balance exceeds the statutory book value, there will be a tax loss in the last period that is not an accounting loss. The tax benefit from that loss can be treated as an asset.

- **DELTA_DTA:** DTA − prior DTA.

- **DEFICIENCY:** This represents the change to current surplus. For all periods before 12/31/24, the DEFICIENCY is set to 0 since past events have no impact on current surplus. For projected dates, DEFICIENCY = 1.0347 × prior DEFICIENCY + STAT_INCOME_POST_TAX + REALIZED_LOSS_BV − 21% × REALIZED_LOSS_BALANCE + DELTA_DTA. Because C-1 assumes a discount factor of 3.47%, the deficiency is assumed to accumulate at a rate of 3.47% so that the present value is not artificially contracted by the delay of losses (the accumulation and discounting offset one another). When taxes exceed the statutory income, the statutory income is negative and contributes to deficiency. When a loss is realized at the end, REALIZED_LOSS_BV is negative and contributes to the deficiency but is offset by the tax benefit on the lost balance.

- **DEFICIENCY_PV:** The present value of deficiency, DEFICIENCY / 1.0347^t, where t is the time (in years) since 12/31/24.

The maximum deficiency is −1 × min(DEFICIENCY_PV) since deficiency is a negative value when a loss occurs. The ratio of the maximum deficiency to the 12/31/24 book value constitutes the C-1 Factor. Like the bond factors, the aggregated C-1 Factor estimates CTE90 and is based on the 17 tail scenarios and derived from the Riemann sum.

While equity does not typically back liabilities, the Academy added the option to assume that the security is liability-backing. All of the calculations run identically, except the DEFICIENCY field only adds STAT_INCOME_POST_TAX if it is negative. The model assumes that if statutory income is positive, the excess cash flow goes towards paying off a liability rather than offsetting deficiency in surplus.

As mentioned, the practical expedient accounting follows the exact same logic with book yield forced to 0%.

5.2 Modeled Debt C-1 Factors by Comparable Attributes

The Academy seeks to identify comparable attributes across CLO debt tranches that can be used to prescribe C-1 Factors. In the ACLI/MA Bond Model, agency ratings serve as the fundamental comparable attribute.

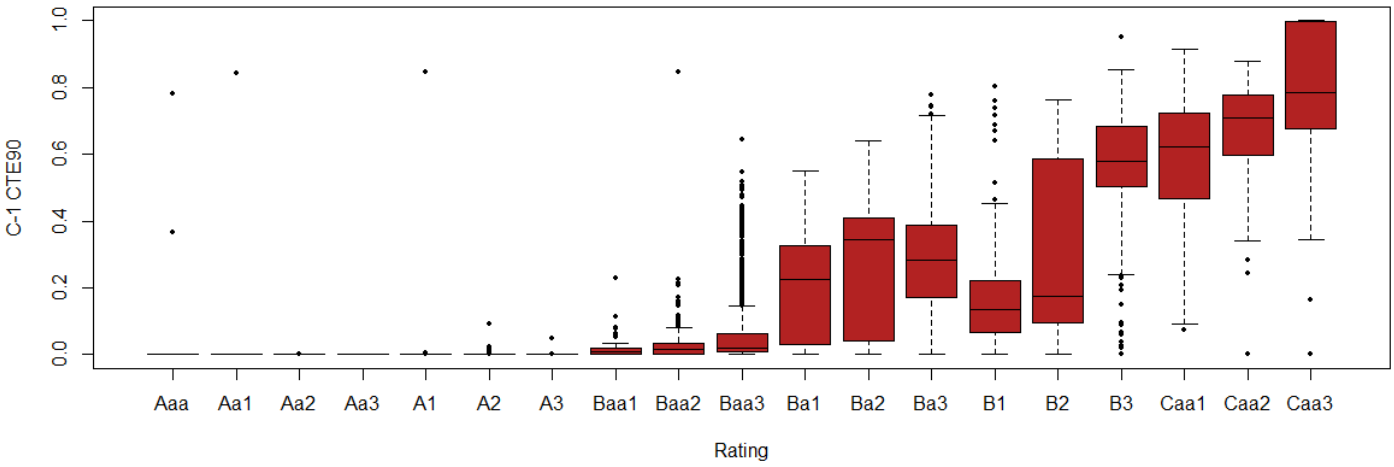
The Academy uses OLS regression models to test various combinations of comparable attributes and to produce Modeled C-1 Factors.

As detailed in Appendix G, the Academy observes that a ratings-only model has better explanatory power than a regression against all other comparable attributes combined, absent data transformations. Accordingly, the Academy first develops the ratings-only model and seeks to identify attributes that contain explanatory power orthogonal to agency ratings.

5.2.1 Ratings-Only Base Model

When the Academy groups Raw C-1 Factors by rating, several observations are immediately apparent that suggest ratings do not sufficiently explain the variance of factors.

Figure 6 - CLO Debt Raw C-1 Factors by Tranche Rating



As illustrated in the Figure 6 box plot:

(1) **Aa3:** has no non-zero observations
(2) **A3:** has fewer extreme outlier points than the adjacent ratings
(3) **Baa3:** has the highest proportion of outlier points
(4) **Ba3/B1/B2:** do not increase monotonically

Some of the observed anomalies are explained by credibility issues. As will be explained later, this is the Academy's conclusion with respect to A/above ratings. The other explanation is hidden covariates not captured by rating.

5.2.2 Identifying Most Explanatory Covariate

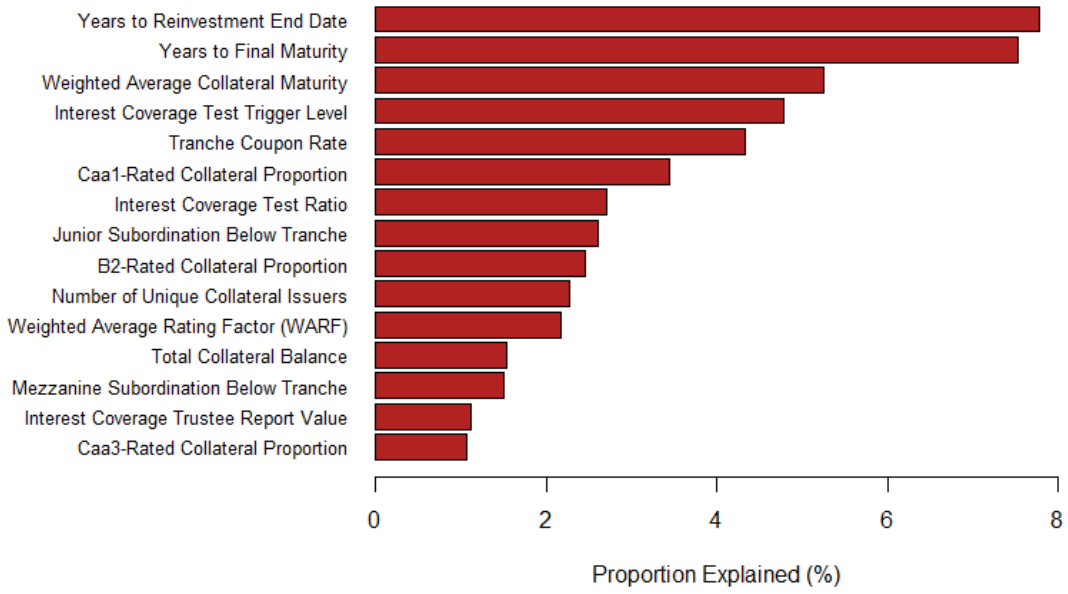
To test the presence of such potential covariates, the Academy takes the ratings-only model as the reference point and adds in each covariate individually to identify the additional proportion of variance explained. The Academy elects to use an OLS regression for this process. Simple "average" is by definition a least-squares solution ("median" is a least-magnitude solution); therefore, regressing the Raw C-1 Factors against dummy variables (i.e., indicators that equal 1 if true and 0 if false) for each rating is identical to

running a simple average by rating. The OLS framework allows the Academy to add additional factors into the model and monitor the variance of residual error to evaluate relative goodness of fit.

When running these iterative regressions, and filtering down to the top 15 most explanatory covariates (without transformation), a clear story emerges: the predominant source of explained variance not captured by ratings is time to maturity. The top three covariates are the years until reinvestment end date, until final maturity and until average collateral maturity. All three are highly correlated; therefore, it is sufficient to choose one.

The Academy chooses **reinvestment end date** given that: 1) it is the most explanatory covariate; 2) it is easier to compute than collateral maturity; and 3) it is more objective than final maturity. Final maturity is chosen for legal contractual purposes and does not represent the time principal is actually repaid due to prepayments. By contrast, the reinvestment end date drives the timing in principal repayment and is integral to the CLO's structure.

Figure 7 - Proportion of Added Explained Variance, Top 15 Predictors (Over Rating)



5.2.2.1 Deriving "Horizon-Neutral" Factors

In the ACLI/MA Bond Model, time to maturity is mechanically ignored. All bonds are treated as having maturities greater than 10 years; when a default occurs, it is assumed that an identical bond with maturity greater than 10 years replaces it. Defaults are modeled based on generic issuers by rating. Because the CLO model relies on real-world securities rather than hypothetical instruments, the Academy's results have the impact of maturity embedded within them.

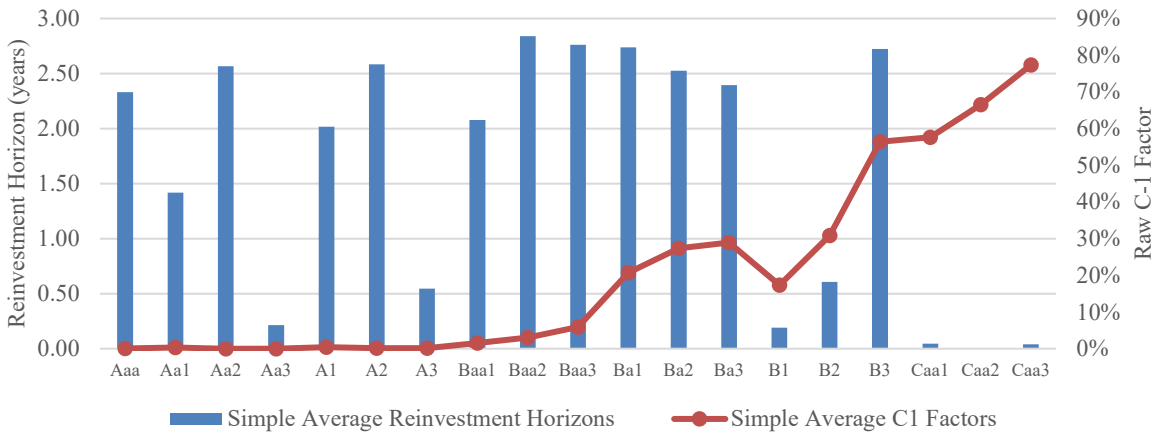
To maintain continuity with the logic of the ACLI/MA Bond Model, the Academy determines that CLO factors should be **horizon-neutral.** That is to say, if two CLO debt tranches are otherwise identical but one has a shorter time to reinvestment end date, they should receive the same C-1 Factor despite the shorter CLO having less risk (due to its shorter horizon).

This can be cleanly accomplished within the OLS framework by regressing Raw C-1 Factors against both rating and the "reinvestment horizon" (years until reinvestment end date) and then fixing the reinvestment horizon to a universe average. For example, an A3 bond's Modeled C-1 Factor would equal the A3 dummy coefficient + reinvestment horizon coefficient × average reinvestment horizon.

This approach would be inappropriate should there exist correlation between agency rating and reinvestment horizon. For example, assume hypothetically that bonds were automatically upgraded when the reinvestment end date was reached. Then higher-rated bonds would have mechanically shorter reinvestment horizons. It would be inappropriate to assign the average horizon to the AAA bonds because the AAA bonds would necessarily have a below-average reinvestment horizon.

The Academy used a Pearson's Product-Moment Correlation Coefficient Test to evaluate this concern. This test found a correlation between reinvestment horizon and numeric agency rating (Aaa = 1, …, Caa3 = 19) of -1.2% with a p-value of 19.1%. This weak correlation and failure to identify statistical significance indicate that reinvestment horizon does not meaningfully trend with rating. Therefore, the Academy elects to use a simple average reinvestment horizon across all ratings, 2.395 years.

Figure 8 - Reinvestment Horizon and Raw C-1 Factors by Rating



When the Academy plots the average Raw C-1 Factors against rating as well as the reinvestment horizons, it becomes plausible that the lack of monotonicity in the Ba3–B3 range is attributable to disproportionately short reinvestment horizons. Unfortunately, a simple regression against ratings and reinvestment horizon does not automatically solve this.

5.2.2.2 Interaction Between Ratings and Horizon

In the below table, the "Baseline" factors are the simple averages by rating. The "No Interaction" column adds in reinvestment horizon as a covariate without any interaction terms. The result is erratic implied factors, e.g., −0.22% for Aa2 and 2.57% for A3. This suggests that the relationship between C-1 and reinvestment horizon is not strictly linear; since the lower-credit-quality bonds have greater variation in C-1, they have greater sensitivity to horizon. If one coefficient is used across all ratings, A/above rated securities are treated as if they have the same variance as high-yield bonds.

Table 5 - Modeled C-1 Factors (%) Regressed against Ratings, Reinvestment Horizon and Interactions

	Baseline	No Interaction	IG/HY	Rating Letters	Proposed Buckets	Alternative Buckets	Ratings Granular
Aaa	0.03	0.12	0.07	0.03	0.03	0.03	0.03
Aa1	0.28	1.58	0.80	0.27	0.27	0.27	0.18
Aa2	0.00	-0.22	-0.09	0.00	0.00	0.00	0.00
Aa3	0.00	2.88	1.15	-0.04	0.04	0.04	0.00
A1	0.40	0.90	0.60	0.41	0.41	0.41	0.35
A2	0.11	-0.14	0.01	0.10	0.10	0.10	0.10
A3	0.12	2.57	1.10	0.16	1.45	0.16	0.05
Baa1	1.58	2.00	1.75	2.25	1.81	1.81	1.80
Baa2	3.02	2.44	2.79	2.08	2.70	2.70	2.69
Baa3	5.94	5.46	5.75	5.17	4.83	4.83	5.01
Ba1	20.70	20.25	18.95	18.60	19.66	19.66	18.43
Ba2	27.37	27.20	26.71	26.58	26.98	26.98	26.27
Ba3	28.92	28.92	28.92	28.92	28.92	28.92	28.92
B1	17.34	20.25	28.61	18.98	30.84	30.84	40.14
B2	30.81	33.17	39.95	32.13	41.76	41.76	63.83
B3	56.39	55.96	54.72	56.15	56.68	56.68	56.61
Caa1	57.60	60.70	69.61	5.00	55.57	55.57	32.87
Caa2	66.51	69.67	78.76	12.89	64.45	64.45	-15.45
Caa3	77.33	80.44	89.37	24.59	75.30	75.30	-3.27
Adjusted R^2	74.69	80.35	83.22	84.77	84.82	84.82	85.47

As an illustration, the "IG/HY" column adds an interaction term for IG assets. This means the factors by rating are derived from the rating coefficient plus the reinvestment horizon coefficient, adjusted for the dummy times average time to reinvestment. Using Baa3 and Ba1 as examples (numbers from Table 6):

- **Baa3:** $0.0449 + (0.0511 - 0.0459) \times 2.395 =$ **5.75%**
- **Ba1:** $0.0670 + (0.0511) \times 2.395 =$ **18.95%**

The −0.0459 component is the IG interaction term, which adjusts the coefficient on reinvestment horizon down to reflect the lower sensitivity in the IG range.

Table 6 - Modeled C-1 Factor vs. Rating, Reinvestment Horizon and IG Flag × Reinvestment Horizon

Parameter	Estimate	Std. Error	t-value	p-value
Aaa	−0.0119	0.0016	−7.66	1.95e−14
Aa1	−0.0046	0.0044	−1.05	0.2942
Aa2	−0.0135	0.0020	−6.66	2.85e−11
Aa3	−0.0011	0.0091	−0.12	0.9015
A1	−0.0066	0.0049	−1.35	0.1755
A2	−0.0125	0.0021	−5.87	4.59e−09
A3	−0.0016	0.0117	−0.14	0.8895
Baa1	0.0049	0.0059	0.83	0.4055
Baa2	0.0153	0.0041	3.68	0.0002
Baa3	0.0449	0.0020	22.11	< 2e−16
Ba1	0.0670	0.0073	9.14	< 2e−16
Ba2	0.1446	0.0088	16.53	< 2e−16
Ba3	0.1667	0.0028	58.99	< 2e−16
B1	0.1636	0.0061	27.00	< 2e−16
B2	0.2770	0.0148	18.78	< 2e−16
B3	0.4247	0.0048	88.59	< 2e−16
Caa1	0.5736	0.0106	53.96	< 2e−16
Caa2	0.6651	0.0105	63.19	< 2e−16
Caa3	0.7713	0.0099	78.14	< 2e−16
REINV_END_DATE	0.0511	0.0009	57.48	< 2e−16
REINV_END_DATE_IG	−0.0459	0.0010	−46.89	< 2e−16

Unfortunately, the IG interaction term does not preclude the model from producing abnormal results, including negative charges for certain A/above ratings. One might consider, as a potential solution, including interaction terms with each rating. This would, in effect, regress Raw C-1 Factors against reinvestment horizon independently for each rating. The results are shown in the final column, "Ratings Granular." Unsurprisingly, the Modeled C-1 Factors for B1 and below become erratic with the Caa2 charge flipping negative. The adjusted R^2 is the highest among the considered models, but it is evidently the product of overfitting and the model should be discarded.

The three middle columns in Table 5 seek to reconcile the approaches by presenting three alternate groupings:

	Rating Letters	Proposed Buckets	Alternative Buckets
Bucket 1	AAA	AAA	AAA
Bucket 2	Aa1 / Aa2 / Aa3	Aa1 / Aa2	Aa1 / Aa2
Bucket 3	A1 / A2 / A3	Aa3 / A1 / A2	Aa3 / A1 / A2 / A3
Bucket 4	Baa1 / Baa2 / Baa3	A3 / Baa1 / Baa2	Baa1 / Baa2
Bucket 5	Ba1 / Ba2 / Ba3	Baa3 / Ba1 / Ba2	Baa3 / Ba1 / Ba2
Bucket 6	B1 / B2 / B3	Ba3 / B1 / B2	Ba3 / B1 / B2

The first grouping groups together ratings by their letter. This accounts for the fact that a typical CLO only has one tranche per letter (e.g., Aaa, Aa2, A2, Baa3) and so it adds credibility. However, it still produces unintuitive results like the negative C-1 at Aa3 and it fails to fix the monotonicity break at Ba3–B3.

The next column, "Proposed Buckets," is the method proposed by the Academy. One concern with the "Rating Letters" method is that it implicitly groups Caa1/Caa2/Caa3 together; these ratings cumulatively account for less than 0.25% of total CLO debt balance. Adding B3 (implicitly) to this group doubles the group's balance, thus increasing its credibility. However, by removing B3 from Bucket 6, Bucket 6 suffers

credibility concerns. Both B1 and B2 are comparatively small tranches and they are the tranches observed to have compressed horizons. Ba3 is added to Bucket 6. By the same logic, Baa3 is added to Bucket 5 since Ba1 and Ba2 are thin.

This approach successfully fixes the monotonicity across the high-yield ratings. The Modeled C-1 Factors strictly increase from Baa1 to Caa3. Where the approach runs into trouble is in A3. A3 is another tranche that has a compressed reinvestment horizon. Most CLOs are structured with an A2 tranche and Baa3 tranche. This means that there is limited data for A3, Baa1, and Baa2. If Baa3 is moved to Bucket 5, then Bucket 4 will lack a traditionally issued tranche (Aaa goes in Bucket 1, Aa2 goes in Bucket 2 and A2 goes in Bucket 3). A3 could be plausibly grouped in either Bucket 3 (so that it is paired with A2 for better credibility) or in Bucket 4 so that Bucket 4 has more observations. The "Alternative Buckets" column presents this alternative grouping.

The difference between "Proposed Buckets" and "Alternative Buckets" does not yield a decisive narrative. They both meaningfully improve the adjusted R^2 over the baseline and fix the monotonicity in the high-yield ratings. In fact, all factors except the A3 factor are identical in the two models and the adjusted R^2 values are identical. Despite the models being otherwise similar, the A3 charge falls by more than a factor of 9, going from 1.45 to 0.16. The Academy initially proceeded with "Proposed Buckets." This concern is further addressed in Section 5.2.6.

5.2.3 Comparable Attributes Beyond Ratings and Horizon

After adding reinvestment horizon to the OLS as described, the Academy investigated whether other comparable attributes have explanatory power for the remaining variance in C-1. When repeating the exercise of adding factors one by one to the OLS regression (which already includes rating, reinvestment horizon and the interaction terms), the Academy observes:

(1) All other factors individually explain less than 4% of remaining variance
(2) Only coupon rate explains more than 2% of remaining variance
(3) Final maturity and weighted average collateral maturity become less significant
(4) Attachment and detachment points show up with modest explanatory power

Figure 9 - Proportion of Added Explained Variance, Top 15 Predictors (Over Rating and Reinvestment Horizon)

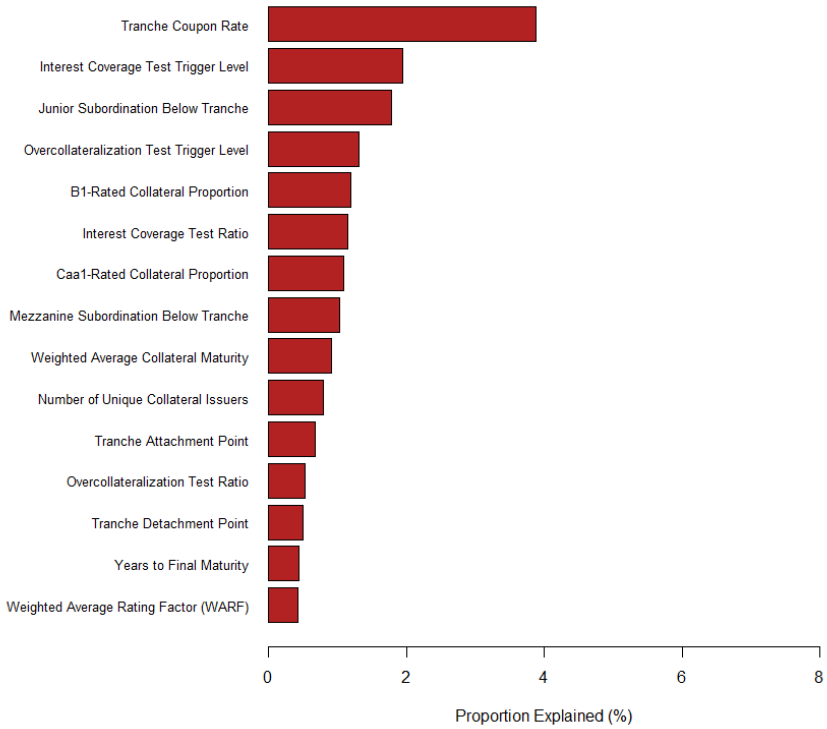


Table 7 - C-1 vs. Rating, Reinvestment Horizon (with Interactions) and Tranche Coupon Rate

	Estimate	Std. Error	t value	Pr(>|t|)
Aaa	-0.0919	0.0045	-20.62	0.000
Aa1	-0.0960	0.0061	-15.79	0.000
Aa2	-0.0960	0.0050	-19.03	0.000
Aa3	-0.1068	0.0097	-11.00	0.000
A1	-0.1046	0.0068	-15.42	0.000
A2	-0.1081	0.0056	-19.29	0.000
A3	-0.1174	0.0121	-9.72	0.000
Baa1	-0.1285	0.0085	-15.19	0.000
Baa2	-0.1206	0.0081	-14.92	0.000
Baa3	-0.1516	0.0062	-24.33	0.000
Ba1	-0.0363	0.0098	-3.70	0.000
Ba2	0.0243	0.0111	2.19	0.029
Ba3	-0.0363	0.0084	-4.34	0.000
B1	-0.0154	0.0096	-1.60	0.109
B2	0.0874	0.0159	5.48	0.000
B3	0.3820	0.0113	33.84	0.000
Caa1	0.3771	0.0132	28.53	0.000
Caa2	0.4635	0.0132	35.07	0.000
Caa3	0.5873	0.0123	47.70	0.000
REINV_END_DATE	-0.0071	0.0021	-3.48	0.001
REINV_END_DATE_1	0.0060	0.0021	2.81	0.005
REINV_END_DATE_2	0.0057	0.0022	2.56	0.011
REINV_END_DATE_3	0.0069	0.0022	3.08	0.002
REINV_END_DATE_4	0.0149	0.0026	5.81	0.000
REINV_END_DATE_5	0.0354	0.0022	15.99	0.000
REINV_END_DATE_6	0.0677	0.0023	29.83	0.000
TR_COUPON	0.0158	0.0007	22.78	0.000

In Appendix G, a litany of regressions run by the Academy are presented with commentary on their comparative advantages.

Since tranche coupon rate is the only attribute with noticeably more explanatory power than the other variables, it is tested as a factor in the OLS. The result is that R^2 increases by 0.71% and the coefficient on the coupon rate is positive (with statistical significance); this is intuitive since it implies that when a CLO has a greater interest obligation, it has a greater risk of loss.

That said, this logic also applies to bonds where coupon rate is not considered as a comparable attribute. Because adding coupon rate does not improve the shape of the fit nor substantially improve R^2 and because it is a clear departure from the bond C-1 framework, the Academy does not affirmatively recommend coupon rate as a comparable attribute.

As noted above, attachment and detachment points (AP and DP) enter the top 15 attributes after adjusting for reinvestment horizon. They only explain ~0.5% of remaining variance, which may suggest that they are not informative. However, a substantial limitation of the single-variable stress test analysis is that it assumes no variable transformation.

At an intuitive level, AP and DP should be able to ballpark the risk profile of a CLO debt tranche by themselves. This is because credit quality of a CLO is secured by its risk-protection structure. AP and DP indicate how much protection each bond has. The reason these do not show up as the most explanatory covariates (over rating) is that they are already implicit in rating. A typical CLO has an Aaa/Aa2/A2/Baa3 structure where each rating corresponds to a general (AP, DP) range.

In Appendix G, it can be seen that if AP and DP are subdivided enough times, they can individually produce R^2 values comparable with that produced by the ratings-only model. For example, if detachment point is subdivided 50 times, then there would be an average factor for bonds with $DP \in [0\%, 2\%)$ and a different charge for $DP \in [2\%, 4\%)$ and so forth. When DP is subdivided 50 times and these subdivisions are added to the Ratings + Reinvestment Horizon (with interactions) model, they increase the adjusted R^2 from 81.63% to 85.63%. This hints that DP may contain non-linear explanatory power.

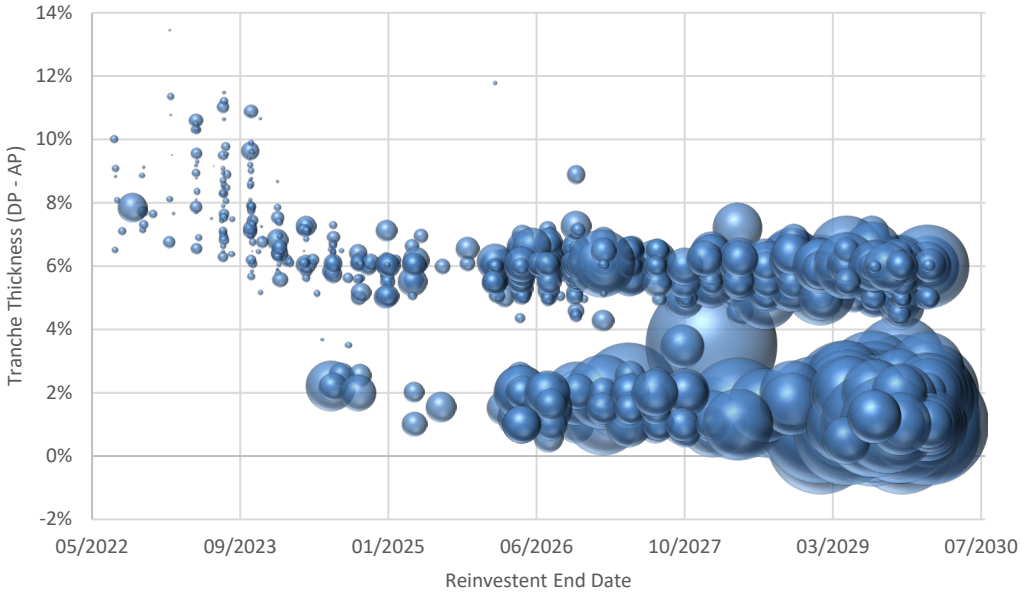
5.2.3.1 Trends in Tranche Thickness

At the top of the section (see Section 5.2.1), four problems with the ratings-only model were flagged. The monotonicity issue was fixed by incorporating reinvestment horizon and the A3 dispersion was addressed (it has a compressed reinvestment horizon). The Baa3 tranche outliers remain an active point of concern, given that Baa3 has a standard average reinvestment horizon.

When plotting C-1 Factors by both reinvestment horizon and "tranche thickness," defined as detachment point (DP) minus attachment point (AP), two clear patterns emerge, particularly in the Baa3 tranche:

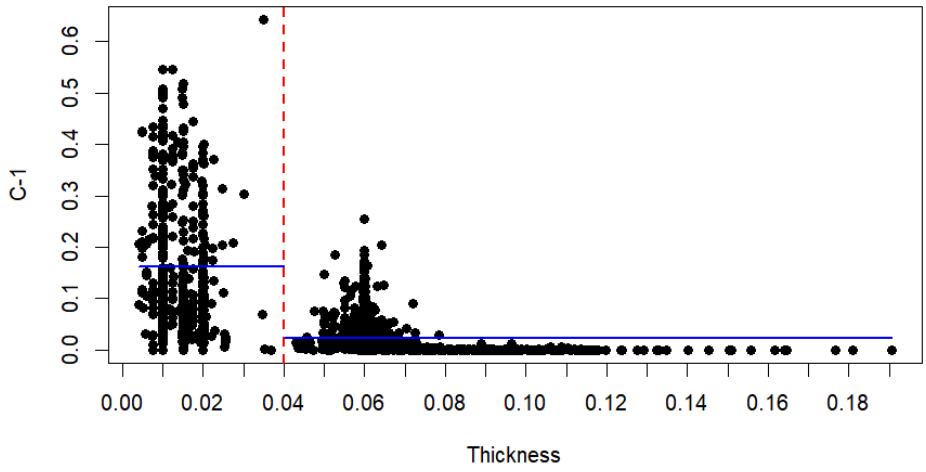
(1) As previously evidenced, C-1 increases as the reinvestment end date moves further out
(2) C-1 is generally greater for thinner tranches, with a clear delineation at ~4% thickness

Figure 10 - Baa3 Raw C-1 Factors vs. Reinvestment Horizon and Tranche Thickness (Bubble Size Indicates C-1 Factor)



When creating a dividing line at 4% and averaging the Raw C-1 Factors for the tranches with ≤4% thickness and with >4%, the delineation in the two groups is even more striking.

Figure 11 - Baa3 Raw C-1 Factors vs. Tranche Thickness



There are no Baa3 bonds that have a thickness between 3.68% and 4.29%; this gap separates two distinct types of Baa3 CLOs. Upon further investigation and from consultation with experts, the Academy learned that the thin tranche is the product of a unique CLO structure that capitalizes on "first-dollar-of-loss" rating methodology. Presented in Table 8 are two CLOs. The "Traditional CLO" has a single Baa3 tranche that roughly covers the ~12–18% range. The Ba3 tranche sits below at the ~8–12% range and the A2 tranche sits above at ~18–24%. To the right is the "Split-BBB CLO." This structure similarly has A2 cover the ~18–24% range and has Baa3 cover the ~12–18% range. The difference lies in the Ba3 tranche. Instead of covering ~8–12%, it covers ~8–11% with a secondary Baa3 tranche in that thin ~11–12% range.

Table 8 - Comparison of CLO Attachment and Detachment Points

Traditional CLO				Split-BBB CLO			
Tranche Name	**Rating**	**Attachment Point**	**Detachment Point**	**Tranche Name**	**Rating**	**Attachment Point**	**Detachment Point**
A1R	Aaa	37.1%	100.0%	AR2	Aaa	35.9%	100.0%
A1J	Aaa	35.1%	37.1%	BR2	Aa2	23.9%	35.9%
A2R	Aa2	24.1%	35.1%	CR2	A2	17.9%	23.9%
BR	A2	18.5%	24.1%	D1R2	Baa3	11.8%	17.9%
CR	Baa3	12.6%	18.5%	D2R2	Baa3	10.8%	11.8%
DR	Ba3	8.1%	12.6%	ER2	Ba3	7.8%	10.8%
PS	NR	0.0%	8.1%	PS1	NR	0.0%	7.8%

If a CLO is rated with "first-dollar-of-loss" methodology, then the severity does not drive the charge; the probability of penetration does. The 11% attachment point for the Split-BBB CLO sits just high enough that its probability of penetration falls in the Baa3 range. But when accounting for severity, the risk for this CLO tranche is much higher than a Traditional Baa3 CLO tranche that detaches at 18%. The "thin" (defined as ≤4% thickness) Baa3 requires only a 12% loss on total collateral to be fully wiped out, while the "thick" (defined as >4% thickness) Baa3 requires an additional 6% of total collateral to be lost in order to be fully wiped out.

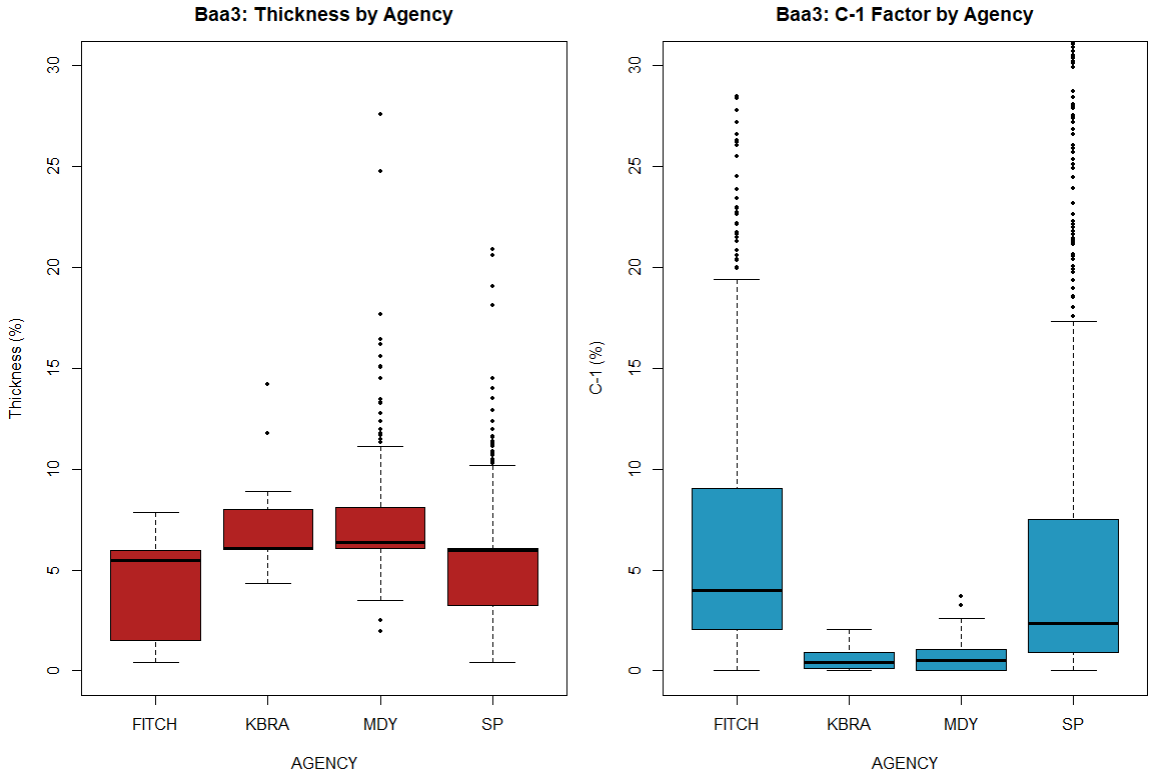
5.2.3.2 Impact of Agency Rating Methodology on Tranche Thickness

This is further illustrated when analyzing the tranche thickness and Raw C-1 Factors by rating agency. S&P and Fitch rate CLOs based on first-dollar-of-loss while Moody's and KBRA rate based on expected losses, which includes assumptions on severity.

The box plots in Figure 12 show the interquartile range (IQR) for each agency. The S&P and Fitch IQRs for tranche thickness sit almost entirely below the Moody's and KBRA IQRs. This means the 25th percentile of tranche thickness for Baa3 ratings from Moody's/KBRA is *as large* as the 75th percentile of tranche thickness for Baa3 ratings from S&P/Fitch. It appears from the data that CLO managers enacting this structure seek ratings from S&P and Fitch to get the extra Baa3 rating. Meanwhile, Moody's/KBRA require the tranches to have the higher detachment point (and thus higher thickness) in order to qualify for the Baa3 rating.

The inverse pattern is reflected in the Raw C-1 Factors. Since S&P/Fitch's Baa3 ratings contain more thin tranches, their Baa3 C-1 Factors skew towards higher risk, given the higher expected severity. The charts are capped at 30% for visualization; not shown are the maximum Fitch and S&P factors, 54.6% and 64.2%, respectively. By contrast, KBRA and Moody's have maximum C-1 Factors of 2.1% and 3.7%, respectively. Similar to the chart with the tranche thickness, the S&P/Fitch IQRs sit almost entirely above the Moody's/KBRA IQRs, once again reaffirming that these are two distinct groups.

Figure 12 - Baa3 Tranche Thickness and Raw C-1 Factor by Rating Agency



To address this phenomenon, the Academy proposes two sets of charges based on tranche thickness. The proposed factors use 4% as the cutoff point, as shown above. This decision is not analytical; 4% is chosen because it is a round number in that range between the two clusters of Baa3 bonds and avoids the pitfall of false precision.

As shown in Appendix H and Appendix I, the gap between Raw C-1 Factors for "thin" and "thick" tranches persists through the lower credit quality. However, the logic used to choose 4% does not neatly apply for those ratings. Ba3, the rating with the most observations below Baa3, has a cluster of bonds issued with 4% thickness. There is a minor cluster of bonds with 4.5% thickness.

For this iteration of the model, the Academy chooses 4% as the cutoff point, to maintain simplicity and avoid false precision. While the analysis is anchored to a 4% cutoff point, the Academy recommends that 4.25% be considered as an alternative cutoff point since 4.25% sits neatly between the 4% and 4.5% peaks observed in Ba3 and still falls in the range of points where Baa3 has no observations. Appendix I presents a detailed comparison of the two options. There is no impact on Baa3 (since there are no observations between 4% and 4.25% thickness). The 4.25% cutoff does better differentiate the risks for Ba3, increasing the gap between "thin" and "thick" charges by over 3 percentage points.

Furthermore, the Academy notes that the tranche thickness analysis is based on the universe of CLOs analyzed. The tranche thickness cutoff point and relevance should be reevaluated if CLO structures materially evolve in the future.

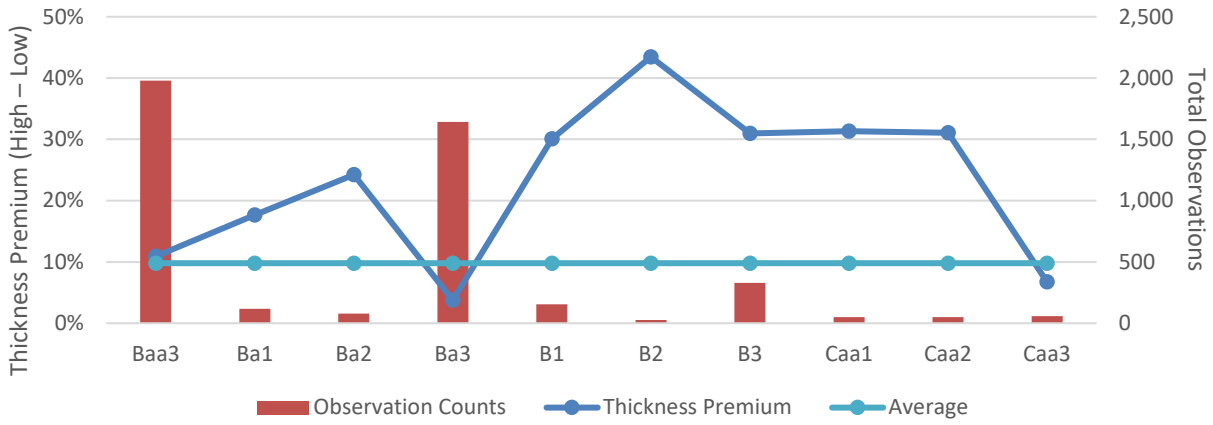
5.2.4 Tranche Thickness (Thick vs. Thin) as a Comparable Attribute

The numbers of "thin" Baa1 and Baa2 tranches are 15 and 14, respectively. These are too infrequent to be credible, so the Academy elects to only evaluate the effect of thickness on C-1 Factors for ratings Baa3 and below.

In the OLS framework, the Academy regresses C-1 against rating, reinvestment horizon (and the interaction terms) and dummy (indicator) variables for thickness ≤ 4% with rating Baa3/below. The coefficients on the "thin tranche" dummy variables are denoted the "thickness premium" since the coefficient indicates how much the C-1 Factor increases for thickness ≤ 4% (compared to thickness > 4%).

The Academy observes that the thickness premium varies across ratings. However, the data is thin for tranches below Ba3. Furthermore, when thickness premium is averaged across ratings Baa3 and below, it is roughly equal to the thin Baa3 premium at ~10%. The Academy concludes that using a single premium for thin Baa3/below debt is sufficient; it does not materially under- or overestimate the premium for the Baa3 level and it reduces the noise for lower-quality debt, where there are fewer observations.

Figure 13 - Distribution of Thin Tranches (≤4%) by Rating



The resulting OLS output is as follows:

Figure 14 - Regression Results Final C-1 Factor Model

```
Residuals:
     Min       1Q   Median       3Q      Max
-0.70926 -0.00145 -0.00037  0.00031  0.84095

Coefficients:
                      Estimate Std. Error t value Pr(>|t|)
Aaa                  6.039e-04  1.788e-03   0.338   0.7356
Aa1                  3.094e-03  4.138e-03   0.748   0.4547
Aa2                  4.661e-04  2.672e-03   0.174   0.8615
Aa3                 -3.794e-05  8.282e-03  -0.005   0.9963
A1                   3.657e-03  4.713e-03   0.776   0.4378
A2                   6.176e-04  2.863e-03   0.216   0.8292
A3                  -2.676e-03  1.069e-02  -0.250   0.8024
Baa1                 9.042e-04  6.104e-03   0.148   0.8822
Baa2                 9.849e-03  5.556e-03   1.773   0.0763 .
Baa3                -1.735e-02  2.705e-03  -6.416 1.45e-10 ***
Ba1                  8.131e-02  6.768e-03  12.014  < 2e-16 ***
Ba2                  1.647e-01  7.998e-03  20.588  < 2e-16 ***
Ba3                  1.286e-01  2.845e-03  45.206  < 2e-16 ***
B1                   1.562e-01  5.507e-03  28.356  < 2e-16 ***
B2                   2.477e-01  1.342e-02  18.461  < 2e-16 ***
B3                   4.999e-01  7.064e-03  70.771  < 2e-16 ***
Caa1                 5.079e-01  9.850e-03  51.564  < 2e-16 ***
Caa2                 5.787e-01  9.871e-03  58.624  < 2e-16 ***
Caa3                 7.349e-01  9.033e-03  81.356  < 2e-16 ***
REINV_END_DATE      -1.115e-02  2.000e-03  -5.575 2.53e-08 ***
REINV_END_DATE_1     1.102e-02  2.087e-03   5.281 1.31e-07 ***
REINV_END_DATE_2     1.097e-02  2.169e-03   5.055 4.37e-07 ***
REINV_END_DATE_3     1.132e-02  2.191e-03   5.168 2.40e-07 ***
REINV_END_DATE_4     1.832e-02  2.491e-03   7.354 2.04e-13 ***
REINV_END_DATE_5     2.977e-02  2.170e-03  13.721  < 2e-16 ***
REINV_END_DATE_6     5.467e-02  2.251e-03  24.282  < 2e-16 ***
LOW_QUAL_LOW_THICK   9.795e-02  2.780e-03  35.233  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.06828 on 12859 degrees of freedom
Multiple R-squared:  0.8618,    Adjusted R-squared:  0.8615
F-statistic:  2970 on 27 and 12859 DF,  p-value: < 2.2e-16
```

Security rating

Reinv horizon

Interaction terms

Quality and thickness

The "LOW_QUAL_LOW_THICK" variable is a dummy equal to 1 when thickness ≤ 4% and credit quality is Baa3 or below, as described above. Each rating is a dummy equal to 1 for bonds with that rating and equal to 0 otherwise. The REINV_END_DATE equals the average years to reinvestment end date and the subsequent interaction terms equal that average when the rating falls in the corresponding bucket (and equals 0 otherwise).

Consider the following examples as illustrations of the mathematical interpretation of the Final Regression C-1 Factor Model:

- Baa1: $0.0009 + 2.395 \times (-0.0111 + 0.0183) = 0.0181 = 1.81\%$
  - The factor for Baa1 is 0.0009.
  - The average reinvestment horizon (across all tranches) is 2.395.
  - The reinvestment horizon coefficient is −0.0111.
  - The reinvestment horizon interaction factor is 0.0183 for Bucket 4 (Baa1 is in Bucket 4).

- "Thick" Baa3: $-0.0174 + 2.395 \times (-0.0111 + 0.0298) = 0.0273 = 2.73\%$
  - The factor for Baa3 is −0.0174.
  - The average reinvestment horizon (across all tranches) is 2.395.
  - The reinvestment horizon coefficient is −0.0111.
  - The reinvestment horizon interaction factor is 0.0298 for Bucket 5 (Baa3 is in Bucket 5).

- "Thin" Baa3: $-0.0174 + 2.395 \times (-0.0111 + 0.0298) + 0.0980 = 0.1253 = 12.53\%$
  - Factors are identical to the "thick" Baa3 charge, except that the premium for thin tranches with rating Baa3/below (0.0980) is added.

Applying this logic to all ratings, splitting out for thickness, results in the following factors:

Table 9 - Modeled C-1 Factors Prior to Isotonic Regression

Rating	Simple Average Raw C-1 Factors	Modeled C-1 Factors	
		Thickness > 4%	Thickness ≤ 4%
Aaa	0.03%	**0.03%**	
Aa1	0.28%	**0.27%**	
Aa2	0.00%	**0.00%**	
Aa3	0.00%	**0.04%**	
A1	0.40%	**0.41%**	
A2	0.11%	**0.10%**	
A3	0.12%	**1.45%**	
Baa1	1.58%	**1.81%**	
Baa2	3.02%	**2.70%**	
Baa3	5.94%	**2.73%**	**12.52%**
Ba1	20.70%	**12.59%**	**22.39%**
Ba2	27.37%	**20.93%**	**30.72%**
Ba3	28.92%	**23.28%**	**33.08%**
B1	17.34%	**26.04%**	**35.84%**
B2	30.81%	**35.20%**	**44.99%**
B3	56.39%	**47.32%**	**57.12%**
Caa1	57.60%	**48.12%**	**57.92%**
Caa2	66.51%	**55.20%**	**64.99%**
Caa3	77.33%	**70.82%**	**80.61%**

For most ratings, the results are salutary. The Modeled C-1 Factors generally improve the monotonicity relative to the simple average of Raw C-1 Factors without meaningfully deviating in magnitude. For the ratings with two modeled factors, the simple average generally sits in the middle of the "thick" and "thin" tranche factors. B1, B2 and Caa2 constitute the exceptions, but these are expected because those three are the ratings for which average reinvestment horizon is noticeably shorter than that of the adjacent ratings (Ba3, B3, Caa1 and Caa3), as previously illustrated.

Appendix G presents the adjusted R^2 for this regression along with all the other regressions considered. This one has an adjusted R^2 of 83.25%. Earlier, tranche coupon was identified as a possible explanatory covariate. After adding the flag for 4% thickness, the coupon only increases adjusted R^2 to 83.71%, less than half a percent. **The marginal increase in explanatory power suggests that rating, reinvestment horizon and tranche thickness are sufficiently explanatory by themselves, producing coherent Modeled C-1 Factors.**

5.2.5 Modeling A3 and Above Tranches

5.2.5.1 Bayesian Frequency/Severity Technique

The remaining concern lies within the A3/above factors, specifically Aa2–A2 where monotonicity fails to materialize. This could indicate that additional comparable attributes are required to explain the factors. However, the cause of this break in monotonicity appears to be benign, driven by standard error.

Table 10 - Raw vs. Modeled C-1 Factors for A3 and Above

	Total Observations	Non-Zero C-1 Observations	Average Raw C-1 Factors	Modeled C-1 Factors
Aaa	3,701	2	0.03%	0.03%
Aa1	297	1	0.28%	0.27%
Aa2	1,879	1	0.00%	0.00%
Aa3	68	0	0.00%	0.04%
A1	246	73	0.40%	0.41%
A2	1,642	844	0.11%	0.10%
A3	41	5	0.12%	1.45%

Aa2 and Aa3 both have simple average Raw C-1 Factors that round to 0.00% with a solitary non-zero observation (out of 1,947 total observations). Even A1, which has 73 non-zero observations, still has credibility concerns when compared to A2, which has over 11 times as many non-zero observations.

A clean potential solution involves Bayesian statistics. As demonstrated in Appendix L, the expected value of non-zero C-1 frequency can be estimated as the number of non-zero observations + 1 divided by the total observations + 2. We can estimate the "implied severity" of non-zero C-1 by taking the ratio of average C-1 to the non-zero frequency. When estimating the "adjusted" Raw C-1 Factors, the Bayesian "expected non-zero frequency" can be multiplied by some estimate of severity. Illustrated in the table are two approaches to severity: using the implied severity from real observations and using the average A3/above severity for all ratings (the average is used in both approaches for Aa3 because it has no non-zero observations).

Table 11 - Bayesian Adjustment for A3 and Above C-1 Factors

	Total Observs	Non-Zero C-1 Observs	Average C-1 Factors	Non-Zero Frequency	Implied Severity	Expected Non-Zero Frequency	Adjusted C-1 (implied severity)	Adjusted C-1 (average severity)
Aaa	3,701	2	0.03%	0.05%	55.52%	0.08%	0.04%	0.00%
Aa1	297	1	0.28%	0.34%	83.16%	0.67%	0.56%	0.00%
Aa2	1,879	1	0.00%	0.05%	0.00%	0.11%	0.00%	0.00%
Aa3	68	0	0.00%	0.00%	N/A	1.43%	0.01%	0.01%
A1	246	73	0.40%	29.67%	1.35%	29.84%	0.40%	0.15%
A2	1,642	844	0.11%	51.40%	0.21%	51.40%	0.11%	0.27%
A3	41	5	0.12%	12.20%	0.98%	13.95%	0.14%	0.07%
Total	7,874	926	0.06%	11.76%	0.52%	11.77%	0.06%	0.06%

It is apparent that this proposal will not solve the problem. While the Aa3 expected frequency is rightly higher than the Aa1 expected frequency (this fixes the Aa3 observed frequency being lower), the Aa2 expected frequency is considerably lower than the Aa1 expected frequency.

Furthermore, the implied severities are closer to 0 for single-A credit, because there are more partial penetrations where the loss is close to, but not exactly, 0. This would suggest that a simple average severity is not appropriate. Unfortunately, the A3/above implied severities do not neatly trend in one direction. If they trended downwards, a curve could be fit to approximate average severity. But as it is, the implied severities are noisy and not credible. Including single-A likely understates the severity for AAA and AA, but excluding single-A would render results that are not statistically credible (since there are only four observations).

5.2.5.2 Isotonic Regression

For these reasons, the Academy concludes that there are insufficient data points to estimate the "true" average Raw C-1 Factor for each A3/above rating. To fix the monotonicity problem, the Academy instead proposes an isotonic regression to compel the Modeled C-1 Factors to increase as credit quality declines. This effectively credibility-weights the factors and relies on real data, reducing the risk of overfitting.

An **isotonic regression** (see Appendix M) forces monotonicity by taking weighted averages of adjacent points. A1, for example, has a Modeled C-1 Factor (after adjusting for reinvestment horizon) of 0.41%. It sits above A2 (in quality), which has a Modeled C-1 Factor of 0.10%. Taking a weighted average—weighting by the number of observations—forces both A1 and A2 to have a factor of:

$$\frac{0.41\% \times 246 + 0.10\% \times 1{,}642}{246 + 1{,}642} = 0.14\%$$

The resulting factors are:

Table 12 - Final Modeled Debt C-1 Factors

Rating	Simple Average Raw C-1 Factors	Modeled C-1 Factors	
		Thickness > 4%	Thickness ≤ 4%
Aaa	0.03%	**0.03%**	
Aa1	0.28%	**0.04%**	
Aa2	0.00%	**0.04%**	
Aa3	0.00%	**0.04%**	
A1	0.40%	**0.14%**	
A2	0.11%	**0.14%**	
A3	0.12%	**1.45%**	
Baa1	1.58%	**1.81%**	
Baa2	3.02%	**2.70%**	
Baa3	5.94%	**2.73%**	**12.52%**
Ba1	20.70%	**12.59%**	**22.39%**
Ba2	27.37%	**20.93%**	**30.72%**
Ba3	28.92%	**23.28%**	**33.08%**
B1	17.34%	**26.04%**	**35.84%**
B2	30.81%	**35.20%**	**44.99%**
B3	56.39%	**47.32%**	**57.12%**
Caa1	57.60%	**48.12%**	**57.92%**
Caa2	66.51%	**55.20%**	**64.99%**
Caa3	77.33%	**70.82%**	**80.61%**

Figure 15 - Comparison of Raw C-1 Factors vs. Proposed Modeled C-1 Factors



5.2.6 Credibility-Weighting Proposed Reinvestment Horizon Adjustments

In Section 5.2.2.2, the Academy accounts for reinvestment horizon and considers two methods for bucketing ratings together, for the purpose of estimating variable interactions. The more conservative approach (resulting in higher C-1), "Proposed Buckets," was used to develop the tranche thickness and isotonic regression models. However, when the Academy re-runs the full script (including tranche thickness parameters and isotonic regression) with the "Alternative Buckets" methodology, the same proposed C-1 Factors are produced, *except* for A3.

Because the resulting A3 factors are quite different, credibility-weighting is appropriate. The Academy

considers the **Akaike Model Averaging** method of credibility-weighting.[22] This method produces credibility weights from the log-likelihood statistics and degrees of freedom. A model's fit is better when it has greater log-likelihood and fewer degrees of freedom, which is reflected in the Akaike Information Criterion (AIC). A model's credibility is greater when its AIC is more negative: when it has the least "information loss." Thus, credibility weights can be derived from AIC.

For the two models considered, the log-likelihoods are:

$$ll_{proposed} = 16{,}316.88 \qquad ll_{alternative} = 16{,}317.14.$$

Because the two models use the same degrees of freedom, it follows that

$$w_{proposed} = \frac{1}{1+e^{ll_{alternative}-ll_{proposed}}} = \frac{1}{1+e^{0.26}} = 44\% \qquad w_{alternative} = 1 - w_{proposed} = 56\%.$$

This would imply a credibility-weighted C-1 Factor for A3 of

$$44\% \times 1.45\% + 56\% \times 0.16\% = 0.72\%.$$

Because both log-likelihood estimates round to 16,317, the Academy concludes that the difference in log-likelihoods may be attributable to random noise and that the simpler and more conservative 50/50 average is warranted. This produces a C-1 Factor for A3 of

$$50\% \times 1.45\% + 50\% \times 0.16\% = \mathbf{0.80}\%.$$

5.3 Modeled Equity C-1 Factors by Comparable Attributes

The Academy began the comparable attributes process for residual tranche equity by observing the dispersion of C-1 Factors.

[22] "AIC Model Selection Using Akaike Weights"; Psychonomic Bulletin & Review; 2004.

Figure 16 - Residual Tranche C-1: Allowable Earned Yield vs. Practical Expedient Distributions

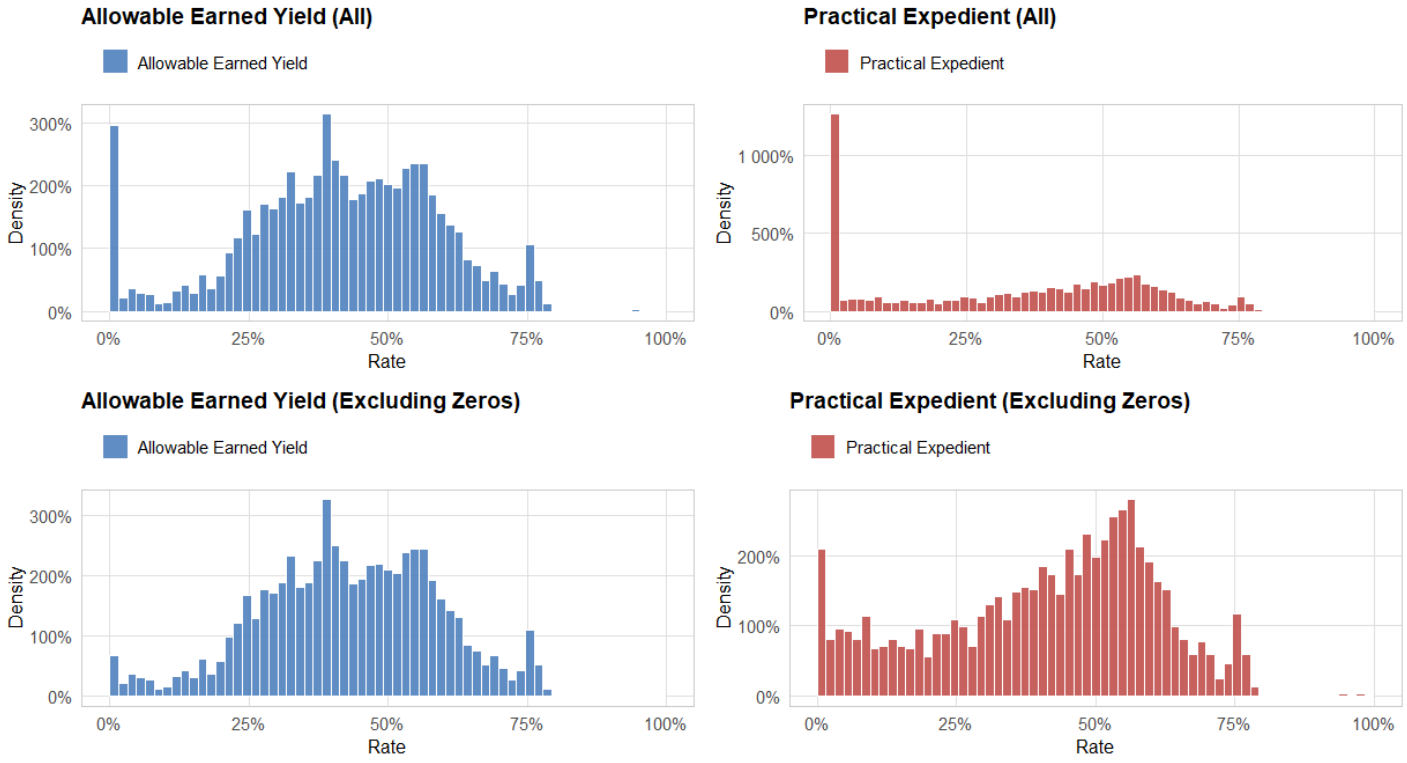


Table 13 - Residual Tranche Raw C-1 Distribution Statistics

	SERIES	PROPORTION ZERO	MEAN	STD DEV	PERCENTILES 5TH	10TH	25TH	50TH	75TH	90TH	95TH
ALLOWABLE EARNED YIELD	Full Universe	3.68%	41.38%	17.77%	3.15%	19.04%	30.80%	41.91%	54.24%	62.62%	69.07%
	Excluding Zeros		42.96%	16.12%	15.84%	23.26%	32.24%	42.90%	54.63%	62.99%	69.19%
PRACTICAL EXPEDIENT	Full Universe	17.26%	33.98%	23.94%	0.00%	0.00%	8.39%	38.72%	54.12%	62.39%	68.90%
	Excluding Zeros		41.07%	20.04%	3.46%	8.76%	27.18%	45.02%	56.10%	63.75%	70.25%

Unsurprisingly, the practical expedient accounting is more likely to result in a book value equal to 0 with no deficiency. When excluding the zero C-1 Factors, the two methods produce very similar factors. This too is unsurprising since the model's embedded conservatism produced low book yields and low book yields approach practical expedient accounting (the two are identical when book yield equals 0, as it does for nearly half of the modeled securities). As a result, the Academy chooses to study only practical expedient accounting. Both methods are valid and practical expedient invokes fewer modeling assumptions, which reduces the risk of added model error.

5.3.1 Considered Comparable Attributes

In consideration of stakeholder suggestions and internal discussions, the Academy first considered the following four comparable attributes:

1. Tranche detachment point: The proportion of losses needed to fully wipe out the residual tranche. A higher detachment point reduces the severity of loss.

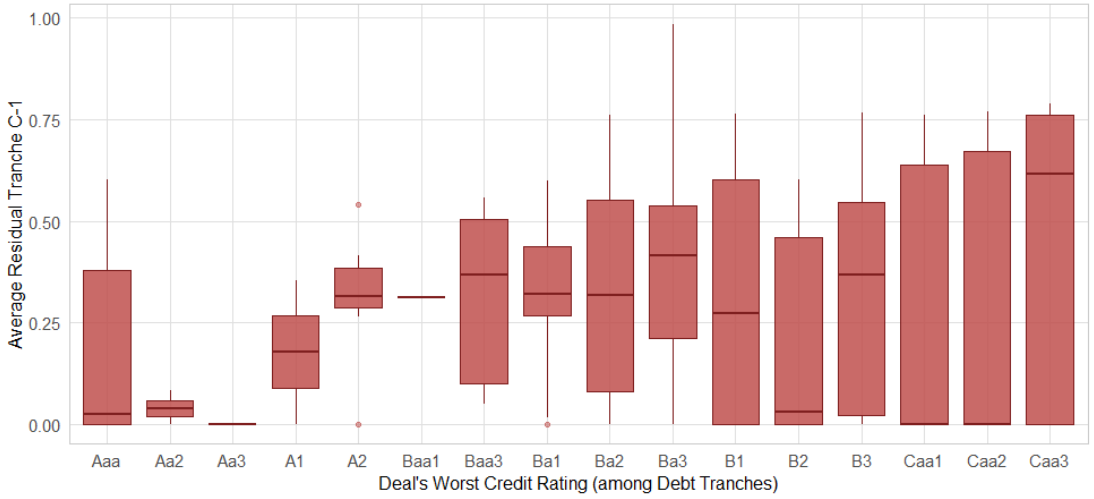
2. WARF: Weighted average rating factor, as defined by Moody's Analytics. A greater factor corresponds to riskier underlying loan credit, increasing tail risk for the residual tranche.

3. Interest/principal-to-face ratio: The ratio of total already paid interest/principal on the residual tranche to the residual tranche face value. This accounts for the fact that residual tranches become less risky as they mature and book value is paid off. When a large portion of face value has already been paid off, the residual tranche is more likely to break even.

4. Maximum rating number: The numeric rating (Aaa = 1, Aa1 = 2, etc.) corresponding to the CLO's lowest-rated debt tranche. CLOs with low-rated debt are expected to place greater risk on the equity tranche.

As shown in Appendix J, the maximum rating number is a poor predictor of C-1. This is further corroborated by Figure 17, which shows that CLOs whose lowest debt rating is Ba3 have higher average residual tranche Raw C-1 Factors than all other CLOs (except for the deals with Caa3 debt).

Figure 17 - Boxplot of Residual Tranche C-1 against Worst Debt Rating



It should be noted that 64.12% of residual tranche securities are part of a CLO whose worst rating is Ba3, so the boxplot is likely skewed by insufficient heterogeneity within the data set.

The Academy considered instead looking at the balance in low-quality ratings. For example, balance in Baa1/below would take the total balance of CLO debt tranches rated Baa1 or worse and divide by the CLO's total balance. This analysis is also shown in Appendix J. The Ba1/below variable has the most explanatory power among the considered thresholds. Detachment point and WARF are no longer statistically significant when the credit quality of the debt tranches is considered.

The Academy reasons that the interest/principal-to-face ratio is a proxy for maturity since a residual tranche closer to maturity will have received more interest than a recently issued residual tranche. Because the C-1 Factors are horizon-neutral, this variable can be set to the mean in any considered formulas. Considering Ba1/below balance as a comparable attribute produces the following formula (after setting the interest/principal-to-face ratio to mean):

27.86% + 1.243 × *Proportion of Ba1/below Balance.*

Two issues emerge when looking at Figure 18 and Figure 19. First, the proportion of Ba1/below balance is concentrated in the small range of (2.5%, 4.5%). Most CLOs—85.67%, to be exact—contain less than 7% of balance in tranches rated Ba1 or below. This means that for 85% of the residual tranches, the C-1 Factor would only range from 27.86% to 36.56%, less than a 10-percentage-point range. Furthermore, the C-1 Factors do not exhibit any clear linear relationship with this attribute. The attribute adds a minor statistical improvement that is dwarfed by the unexplained random noise. For these reasons, the Academy concludes that there is not good evidence in favor of adding a comparable attribute for residual tranche equity.

Figure 18 - Distribution of Proportion of Balance in Ba1/below Credit

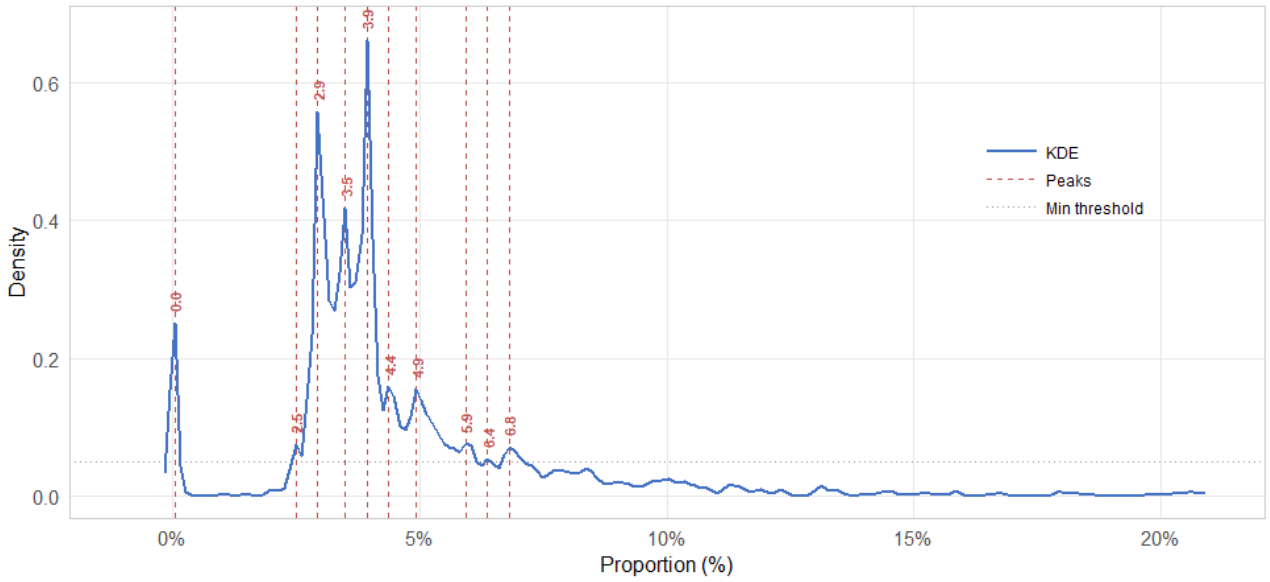
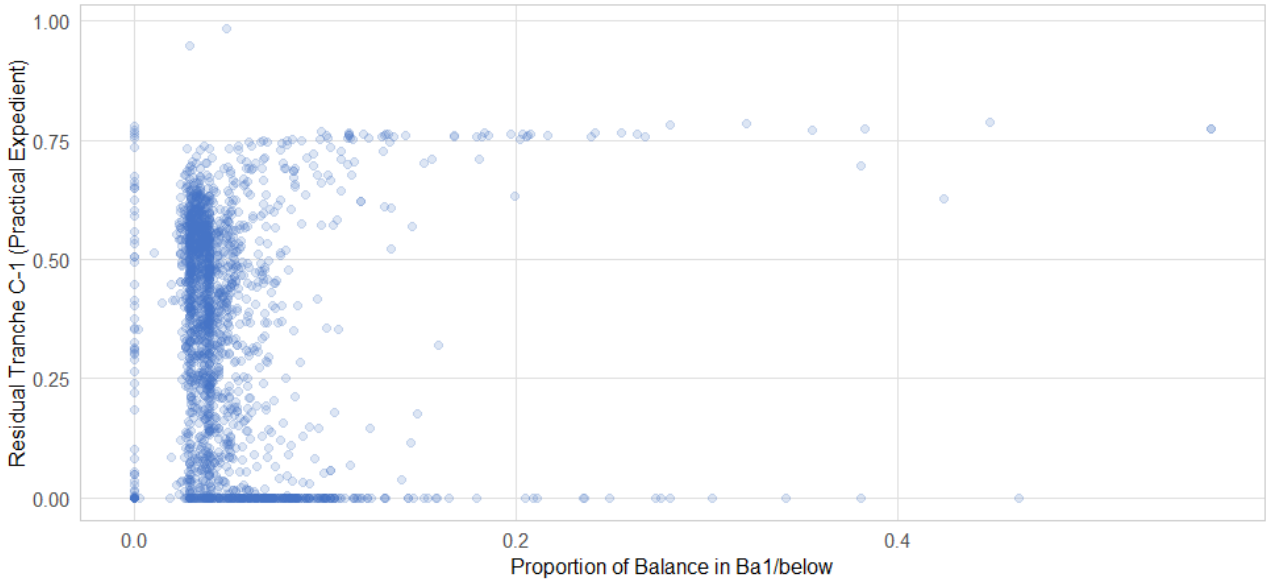


Figure 19 - Residual Tranche C-1 vs. Proportion of Balance in Ba1/below Credit



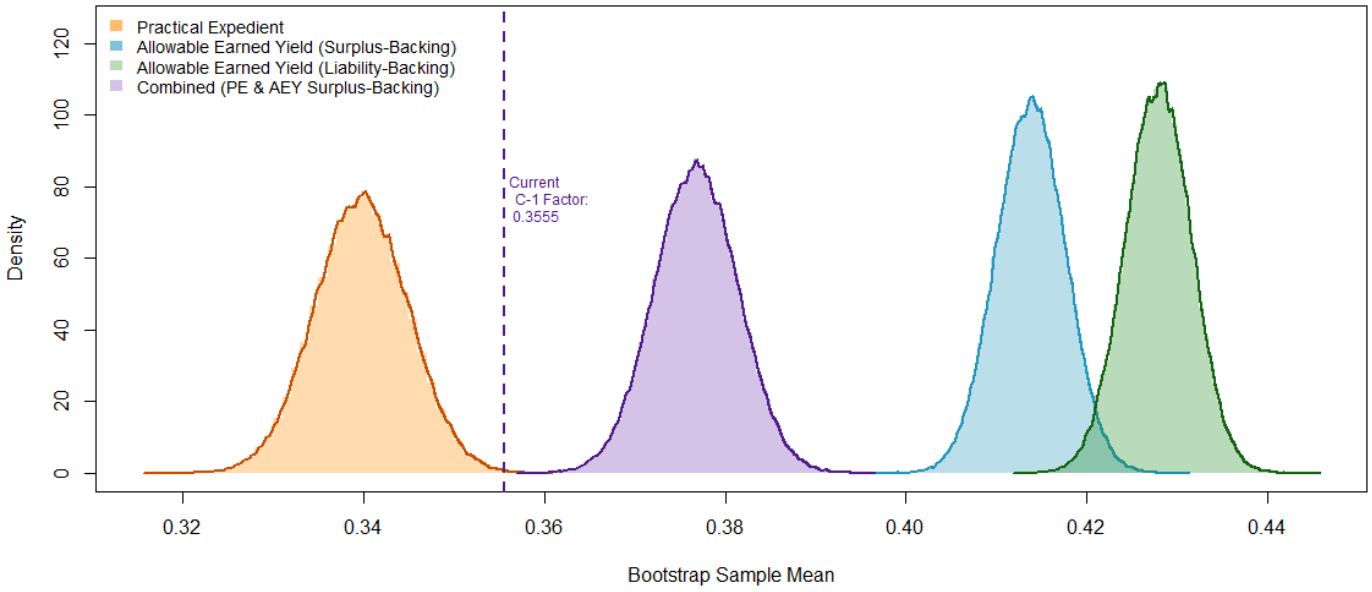
5.3.2 Comparing Average C-1 to Existing Factors

Because the residual tranche C-1 Factors are erratic and do not exhibit patterns like the debt C-1 Factors, the Academy must decide if the evidence in favor of changing the residual tranche factor is even statistically significant.

At the time of this research, the current post-tax residual tranche factor is 35.55%. The modeled range provided in Section 5.3.1 is 27.86% to 36.56%, which includes 35.55%.

The other consideration is sampling error. To estimate the distribution of sample mean, the Academy implements bootstrapping. The three residual tranche accounting methods are plotted. The "combined" histogram represents the average distribution of practical expedient and AEY (surplus-backing).

Figure 20 - Distribution of Estimated Residual Tranche C-1 Means, by Accounting Method



The current 35.55% factor lands between the two accounting methods. The p-value for practical expedient accounting is 0.2%. This indicates that sampling error *alone* does not explain deviation from the 35.55% benchmark. However, sampling error is not the only error within the analysis; the scenario selection (of the 17 tail scenarios) introduces error along with the parameter selection. For these reasons, the Academy concludes that the current 35.55% factor is plausibly within the range of potential average Raw C-1 Factors for residual tranches.

Due to the inconclusive nature of this analysis, the Academy suggests retaining the status quo until better evidence is presented in favor of changing residual tranche factors.

6 Final C-1 Factors

The Academy concludes that the single most explanatory variable with respect to CLO tail risk is agency ratings. The Academy further observes that reinvestment horizon and tranche thickness are not fully captured within the agency ratings, leaving room for additional modifications.

The modeled factors are derived from an ordinary least squares regression of C-1 against dummy variables for rating, against reinvestment horizon with interaction terms by rating and against a dummy variable indicating thickness $\leq 4\%$ and rating Baa3/below. This regression has an adjusted R^2 of 83.25%.

Table 14 - Final Regression Model for Proposed C-1 Factors (Proposed Buckets)

Coefficients on Rating Dummy Variables:

Rating	Coefficient	Std. Error	t-value	p-value
Aaa	0.0006	0.0018	0.34	0.74
Aa1	0.0031	0.0041	0.75	0.45
Aa2	0.0005	0.0027	0.17	0.86
Aa3	0.0000	0.0083	0.00	1.00
A1	0.0037	0.0047	0.78	0.44
A2	0.0006	0.0029	0.22	0.83
A3	-0.0027	0.0107	-0.25	0.80
Baa1	0.0009	0.0061	0.15	0.88
Baa2	0.0098	0.0056	1.77	0.08
Baa3	-0.0174	0.0027	-6.42	1.45E-10
Ba1	0.0813	0.0068	12.01	4.53E-33
Ba2	0.1647	0.0080	20.59	1.08E-92
Ba3	0.1286	0.0028	45.21	0.00E+00
B1	0.1562	0.0055	28.36	1.28E-171
B2	0.2477	0.0134	18.46	3.96E-75
B3	0.4999	0.0071	70.77	0.00E+00
Caa1	0.5079	0.0099	51.56	0.00E+00
Caa2	0.5787	0.0099	58.62	0.00E+00
Caa3	0.7349	0.0090	81.36	0.00E+00

Coefficients on Years to Reinvestment End Date:

Bucket	Coefficient	Std. Error	t-value	p-value
All Ratings	-0.0111	0.0020	-5.57	2.53E-08
Aaa	0.0110	0.0021	5.28	1.31E-07
Aa1 / Aa2	0.0110	0.0022	5.05	4.37E-07
Aa3 / A1 / A2	0.0113	0.0022	5.17	2.40E-07
A3 / Baa1 / Baa2	0.0183	0.0025	7.35	2.04E-13
Baa3 / Ba1 / Ba2	0.0298	0.0022	13.72	1.52E-42
Ba3 / B1 / B2	0.0547	0.0023	24.28	2.18E-127

Coefficient on Low Quality / Low Thickness Dummy

Bucket	Coefficient	Std. Error	t-value	p-value
Thickness ≤ 4% Baa3/below	0.0980	0.0028	35.23	1.12E-259

Table 15 - Final Regression Model for Proposed C-1 Factors (Alternative Buckets)

Coefficients on Rating Dummy Variables:

Rating	Coefficient	Std. Error	t-value	p-value
Aaa	0.0006	0.0018	0.34	0.74
Aa1	0.0031	0.0041	0.75	0.45
Aa2	0.0005	0.0027	0.17	0.86
Aa3	0.0000	0.0083	0.00	1.00
A1	0.0037	0.0047	0.78	0.44
A2	0.0006	0.0029	0.22	0.83
A3	0.0011	0.0107	0.11	0.91
Baa1	0.0006	0.0061	0.10	0.92
Baa2	0.0094	0.0056	1.69	0.09
Baa3	-0.0174	0.0027	-6.42	1.45E-10
Ba1	0.0813	0.0068	12.01	4.51E-33
Ba2	0.1647	0.0080	20.59	1.07E-92
Ba3	0.1286	0.0028	45.21	0.00E+00
B1	0.1562	0.0055	28.36	1.26E-171
B2	0.2477	0.0134	18.46	3.93E-75
B3	0.4999	0.0071	70.77	0.00E+00
Caa1	0.5079	0.0098	51.57	0.00E+00
Caa2	0.5787	0.0099	58.63	0.00E+00
Caa3	0.7349	0.0090	81.36	0.00E+00

Coefficients on Years to Reinvestment End Date:

Bucket	Coefficient	Std. Error	t-value	p-value
All Ratings	-0.0111	0.0020	-5.57	2.53E-08
Aaa	0.0110	0.0021	5.28	1.31E-07
Aa1 / Aa2	0.0110	0.0022	5.05	4.37E-07
Aa3 / A1 / A2	0.0113	0.0022	5.17	2.38E-07
A3 / Baa1 / Baa2	0.0185	0.0025	7.39	1.57E-13
Baa3 / Ba1 / Ba2	0.0298	0.0022	13.72	1.51E-42
Ba3 / B1 / B2	0.0547	0.0023	24.28	2.16E-127

Coefficient on Low Quality / Low Thickness Dummy

Bucket	Coefficient	Std. Error	t-value	p-value
Thickness ≤ 4% Baa3/below	0.0980	0.0028	35.23	1.12E-259

The final factors (for both methods) are derived by rating (split out by "thick" and "thin" tranches for Baa3/below). The dummy for the corresponding rating is set to 1 (all other rating dummies set to 0) with the dummy for low quality/low thickness set to 1 only for the "thin" Baa3/below tranches. For all ratings, the reinvestment horizon is set to the universe average, 2.395, so as to retain horizon neutrality. The resulting factors from the two regressions are averaged together (using simple average), which only has a material impact on A3. Proposed residual tranche factors are kept at current rates. The resulting factors are:

Table 16 - Final Proposed Post-Tax C-1 Factors

Rating	Proposed C-1 Factors	
	Thickness > 4%	Thickness ≤ 4%
Aaa	0.03%	
Aa1	0.04%	
Aa2	0.04%	
Aa3	0.04%	
A1	0.14%	
A2	0.14%	
A3	0.80%	
Baa1	1.81%	
Baa2	2.70%	
Baa3	2.73%	12.52%
Ba1	12.59%	22.39%
Ba2	20.93%	30.72%
Ba3	23.28%	33.08%
B1	26.04%	35.84%
B2	35.20%	44.99%
B3	47.32%	57.12%
Caa1	48.12%	57.92%
Caa2	55.20%	64.99%
Caa3	70.82%	80.61%
Residual Tranche	35.55%	

Assuming a tax rate of 21% with 80% recovery for debt (100% recovery for equity), the Academy calculates the following pre-tax factors:

Table 17 - Final Proposed Pre-Tax C-1 Factors

Rating	Proposed C-1 Factors	
	Thickness > 4%	Thickness ≤ 4%
Aaa	0.04%	
Aa1	0.05%	
Aa2	0.05%	
Aa3	0.05%	
A1	0.17%	
A2	0.17%	
A3	0.97%	
Baa1	2.18%	
Baa2	3.24%	
Baa3	3.28%	15.05%
Ba1	15.14%	26.91%
Ba2	25.15%	36.93%
Ba3	27.99%	39.76%
B1	31.30%	43.07%
B2	42.31%	54.08%
B3	56.88%	68.65%
Caa1	57.84%	69.61%
Caa2	66.34%	78.12%
Caa3	85.12%	96.89%
Residual Tranche	45.00%	

7 Portfolio Adjustment Factors (PAF)

Within the bond model, C-1 Factors were generated for a representative life insurance portfolio. Because issuer diversification affects tail risk, additional factors were generated to estimate the C-1 for insurers that hold more or fewer unique bond issuers than the representative portfolio. The factors are presented in brackets where the first 10 issuers get one factor and the next 90 get a different factor and so forth.

Table 18 - Bond Model Portfolio Adjustment Factors

	Lower Bound	Upper Bound	Factor
First 10	0	10	5.87
Next 90	10	100	1.53
Next 100	100	200	0.85
Next 300	200	500	0.85
501+	500		0.82

Such an analysis of CLOs is not possible for the Academy due to operational limitations. Modeling diversification directly would require more simulations passed through CDOnet in order to estimate the correlations between CLO deals.

In lieu of direct modeling, the Academy seeks mathematical equivalence with the bond model.

For a CLO, the credit risk is driven by underlying loan issuers. Hence the Academy reasons that owning just one tranche of a CLO should receive the same PAF as owning the entire vertical slice—and thus it is fair to model the PAF or diversification at the deal level (i.e., as if the entire vertical slice is owned). This creates mathematical ease because the diversification of the underlying loans passes through directly to the CLO owner. If an insurer owns multiple CLOs, then the insurer gets the diversification benefits of the combined loan portfolios.

The Academy considered modeling different factors by rating or requiring a certain number of tranches to be held by deal for the deal to qualify for the PAF. The argument considered is that the credit risks across tranches may diversify differently than the credit risks across independent bond issuers. It is not clear that an Aa tranche will diversify against a Baa tranche to the same extent that two Baa tranches will diversify against one another. Furthermore, the concentration risk in the underlying data will not penetrate all tranches the same way. If a CLO is concentrated, that could have an outsized effect on the subordinated tranches.

The Academy ultimately decided against this path because: 1) the bond model does not distinguish by rating for PAF, even though similar arguments could be made; and 2) the operational constraints prevent the Academy from deriving credible statistically driven results.

7.1 Modeling CLO PAF

When constructing the 17 scenarios in the Collateral Model, the Academy jointly simulated defaults and recoveries for the full universe of loans and calculated the present value of the full loan universe. In other words, all C-1 calculations for CLOs depended on underlying defaults diversified at the universe level. After filtering down to the U.S. BSL CLOs used for comparable attributes and removing small equity securities from the loan collateral, the Academy observes that across the 2,074 CLOs analyzed, there are 1,957 unique loan issuers. If an insurer held a portfolio containing the full universe of loans underlying CLOs, their PAF would be 88.46% (using the formula from the ACLI/MA Bond Model).

The final CLO C-1 base factors represent the factors for an insurer owning this full universe portfolio, so any CLO PAF applied to a real-world insurance portfolio will be strictly greater than 1, adjusting the factors to a less diversified portfolio.

Because the CLOs have overlapping loan issuers in the underlying portfolios, the Academy first estimates the distribution of number of unique issuers per given number of CLO deals. For a single CLO deal, this is just the total number of unique issuers for the underlying loans. But for two CLOs, the Academy identifies all unique CLO deal pairs, calculates the number of unique loan issuers across both CLOs in each pair and reports the distribution. When addressing portfolios of 3+ CLO deals, there are many combinations, so the Academy randomly samples 10,000 combinations of unique CLOs, calculates the number of unique issuers for each and reports the distribution of the 10,000 simulations.

Given a fixed number of CLO deal holdings, the Academy estimates the distribution of the number of unique loan issuers underlying the CLOs. For each number, the Academy calculates the bond PAF that would be applied to those loans if the insurer owned them directly. The Academy then takes a weighted average based on the distribution to estimate the average PAF for the given number of CLOs.

The Academy defines two PAF metrics. First, *absolute* PAF is defined as the weighted average bond PAF for the loans underlying a portfolio of a given number of CLOs. Second, *relative* PAF is defined as the absolute PAF divided by the collateral universe PAF. The relative PAF assumes full diversification when holding a loan for every one of the 1,957 issuers in the collateral universe.

Figure 21 - Distribution of Unique Loan Issuers per Given Number of CLOs

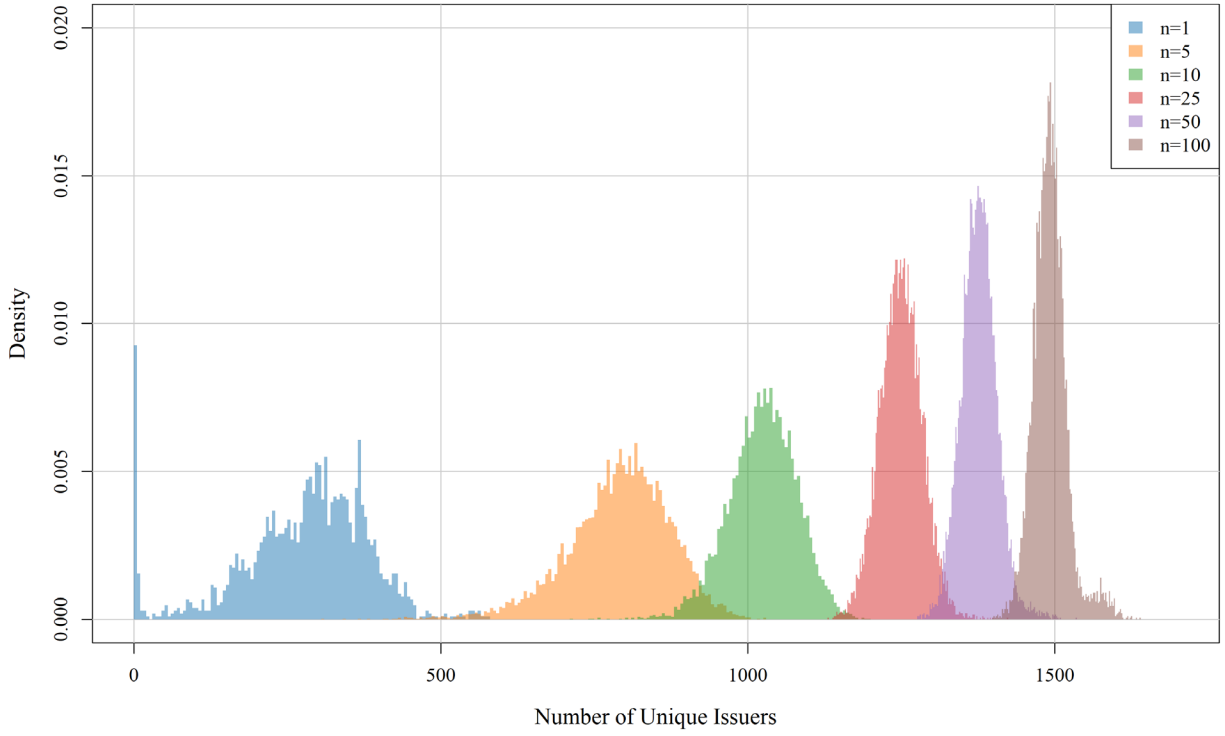
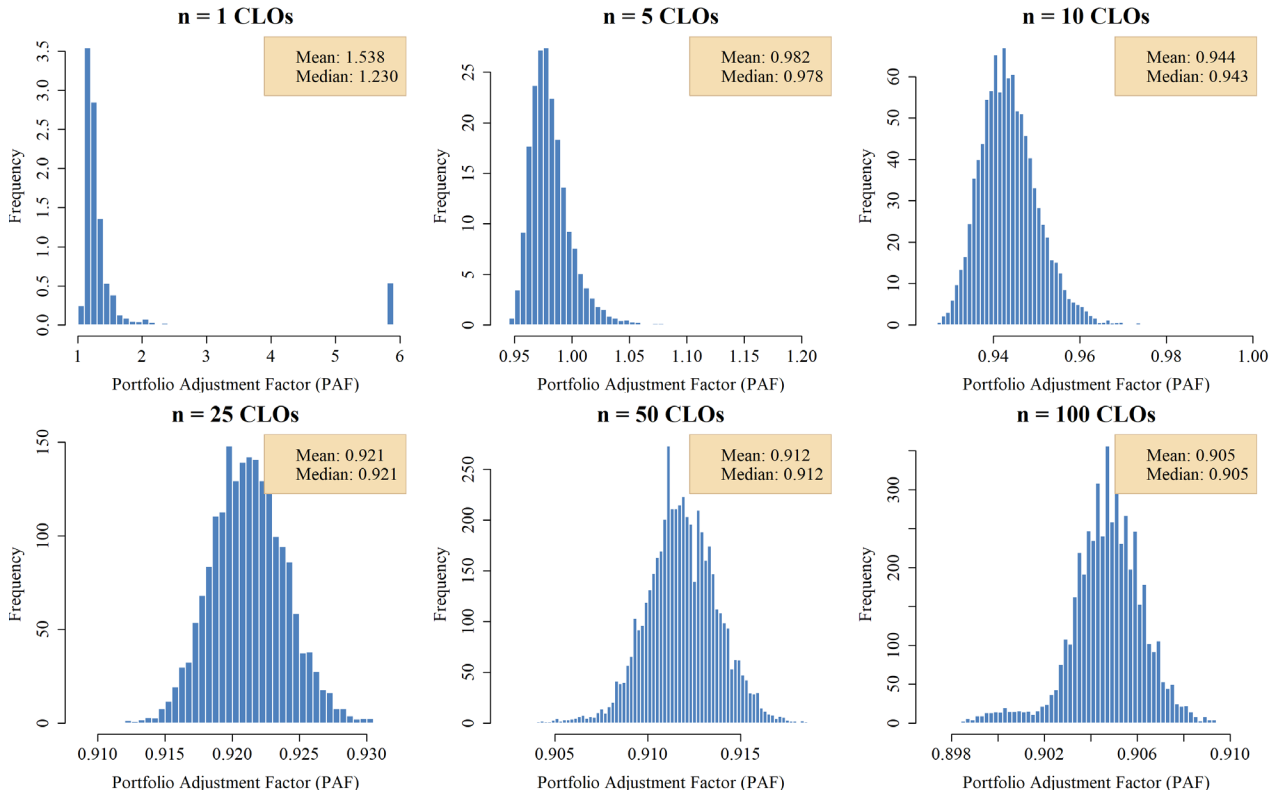
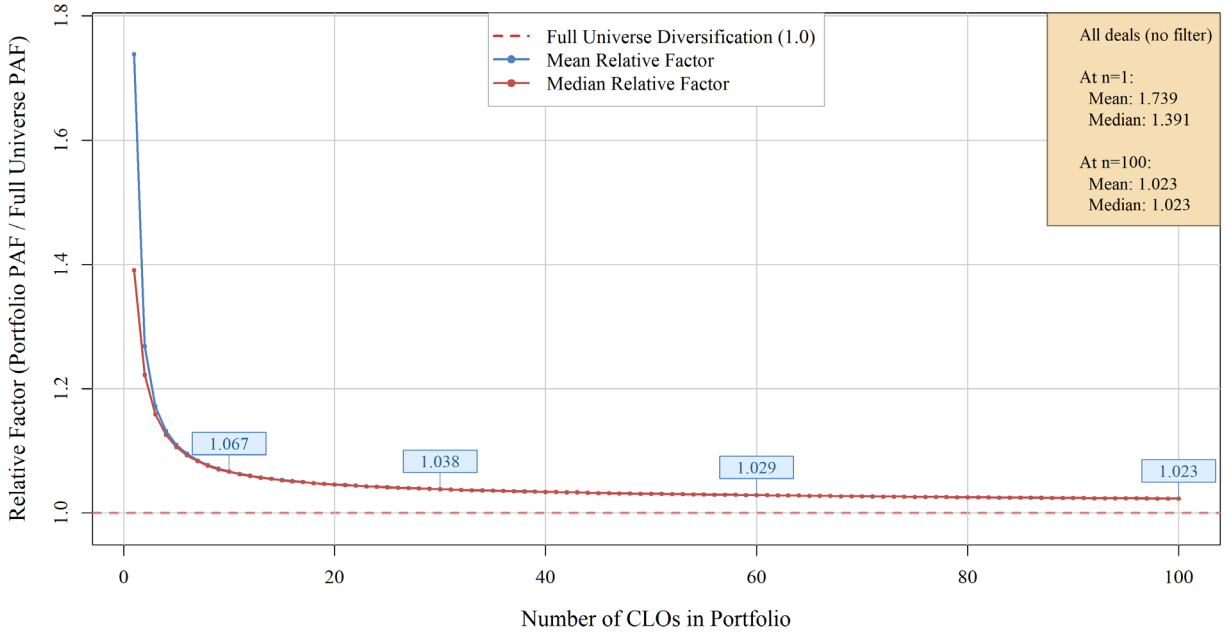


Figure 22 - Distribution of Absolute PAFs by Number of CLOs



Because the base factors are calculated using the fully diversified universe, the *relative* PAFs are the ratio of PAF to full-universe PAF.

Figure 23 - Relative PAF Trend



The Academy observes that the relative PAFs rapidly approach 1. The mean skews above the median for 1–3 CLOs but quickly converges. This is due to a handful of CLOs that have 10 or fewer underlying loan issuers. Those CLOs tend to be older and smaller, so they are not representative of the rest of the universe. The Academy recommends using the median relative PAF to avoid bias from this skew. For the first 10 combinations, the PAFs are as follows:

Table 19 - Absolute vs. Median PAF for ≤10 CLOs

# Unique CLO Deals	Number of Companies*	Median Unique Loan Issuers	Median Absolute PAF	Median Relative PAF
1	20	293	1.7386	1.3907
2	1	482	1.2686	1.2222
3	4	617	1.1712	1.1586
4	7	720	1.1319	1.1254
5	5	798	1.1097	1.1060
6	5	863	1.0951	1.0926
7	7	915	1.0848	1.0831
8	1	959	1.0772	1.0760
9	4	996	1.0714	1.0704
10	2	1,027	1.0668	1.0661

7.2 PAF Implication on Life Insurers

The Academy also seeks to estimate the real-world impact. Relying on 2024 year-end statutory filings and CLO identification based on third-party data sources,[23] the Academy identifies the number of unique CLOs owned by each insurer who owns at least one CLO. This analysis evaluates companies at the group level and does not distinguish between BSL and non-BSL CLOs, nor USD and non-USD CLOs. The Academy observes that a meaningful amount, 56 insurers, hold 10 or fewer CLOs. But the median number of CLOs owned is 40, with the average dragged up by six insurers who own over 500 unique deals.

[23] Sources: S&P Global, Kanerai, Intex, Barclays Research, Pitchbook, JP Morgan, Neuberger.

Figure 24 - Distribution of Number of Unique CLOs, Life Insurers (Group Level)

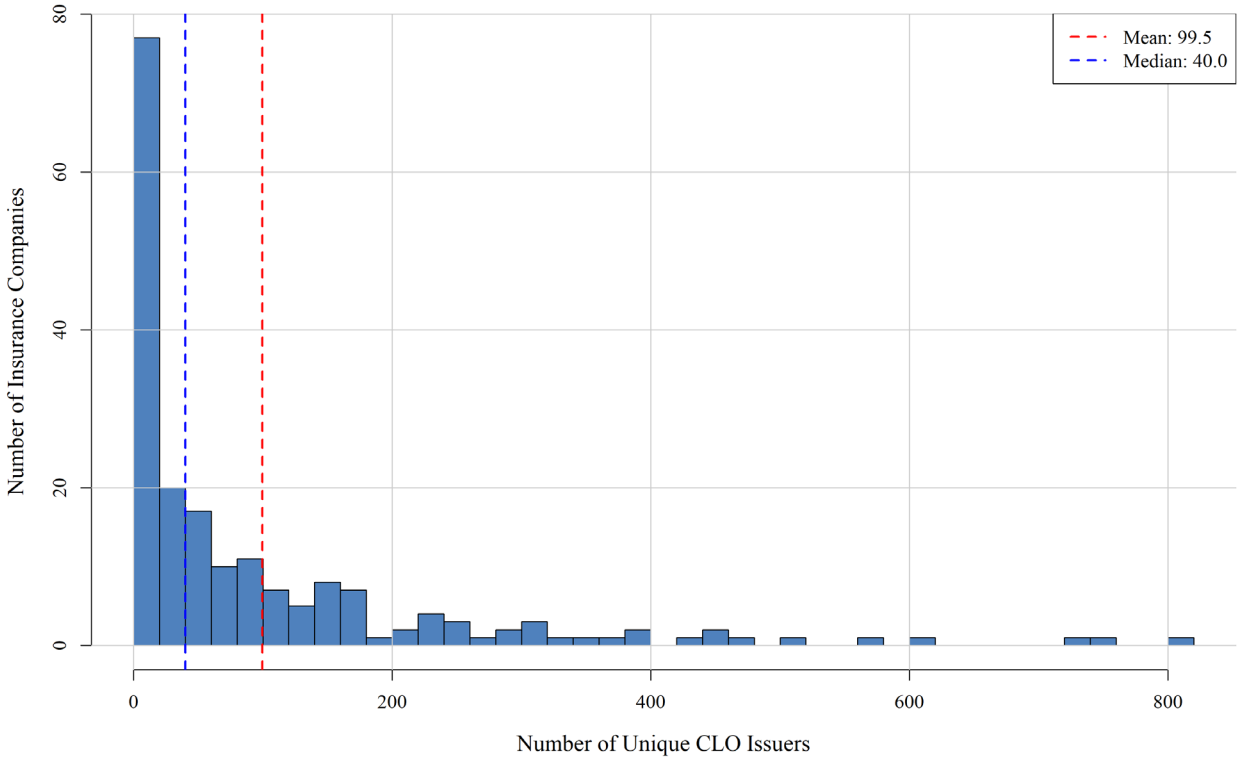


Table 20 - Statistics on Number of Unique CLOs, Life Insurers (Group Level)

Statistic	Value
Total CLO Holdings	27,947
Unique CLO Deals	3,310
Median CLO holdings per co.	51
Median unique CLO deals per co.	40
Standard deviation	145.9
Range	1 to 811 unique CLO deals
Q1 (25th percentile)	7 unique CLO deals
Q3 (75th percentile)	135 unique CLO deals
Unique CLO Deals Count Range	**# of Companies**
1–10	56
11–25	23
26–50	29
51–100	27
101–200	28
201–500	24
501+	6

The Academy also looks at the size and credit quality of CLOs by number of CLOs owned. The purpose of C-1—in addition to being mathematically sound—is to identify real-world concerns of solvency. If the CLOs are small and/or high quality for those insurers with 10 or fewer, there is less immediate cause for concern.

In Figure 25 and Figure 26, the Academy observes two reassuring trends: 1) the proportion of CLO book value (to total *Schedule D1* book value) increases alongside deal diversification, and 2) the credit quality becomes riskier alongside deal diversification. In general, the companies with 10 or fewer—and especially those with 5 or fewer—CLOs have predominantly A3/above credit that is a small portion of bond allocation.

The notable exceptions are the two companies that own only one CLO with rating designations of NAIC 5 and 6. These two companies' CLOs represent less than 0.1% of total general account invested assets. Conversely, there are two companies that have ≤5 CLOs that make up almost 20% of *D1* assets and both of them allocate 100% to NAIC 1A. This data is provided for all life insurers in Appendix N.

With this context, the Academy believes that a PAF cutoff at owning 10 or fewer CLOs suffices and that the insurers owning more than 10 CLOs are sufficiently diversified that PAF is unnecessary.

Figure 25 - Boxplot of CLO Book Value Ratio (to *Schedule D1* BV), by Number of Unique CLOs Owned

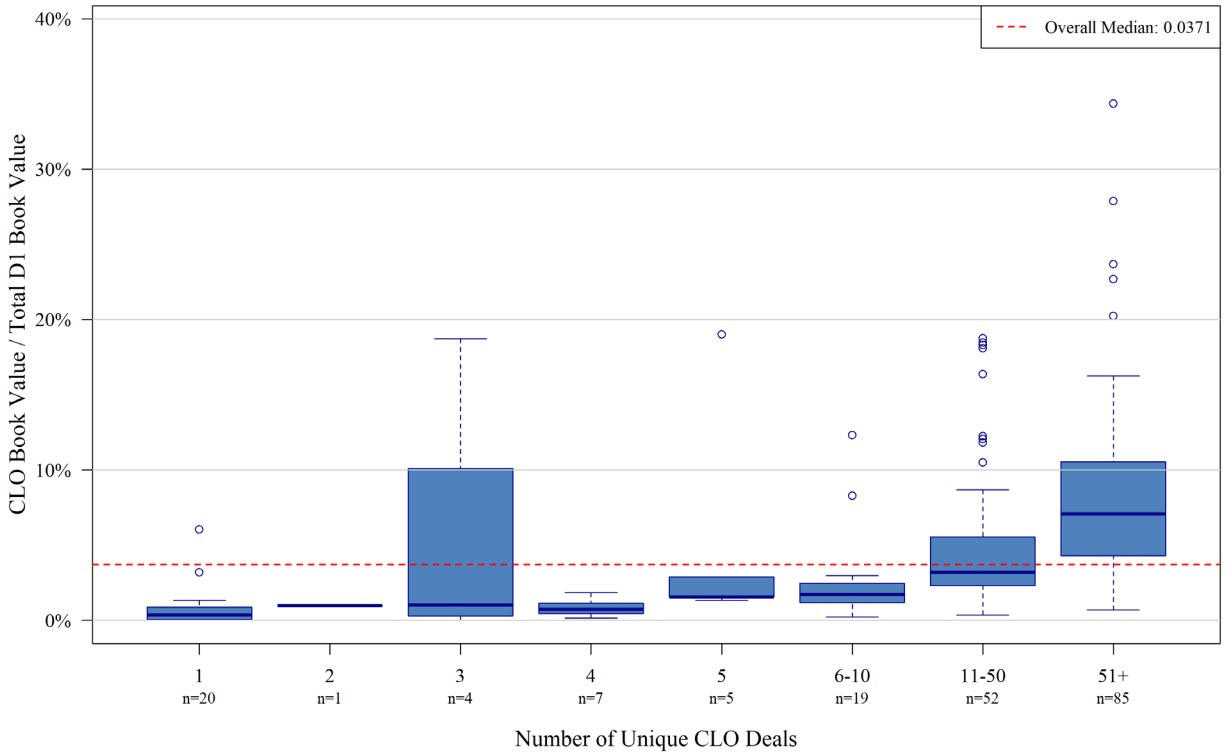
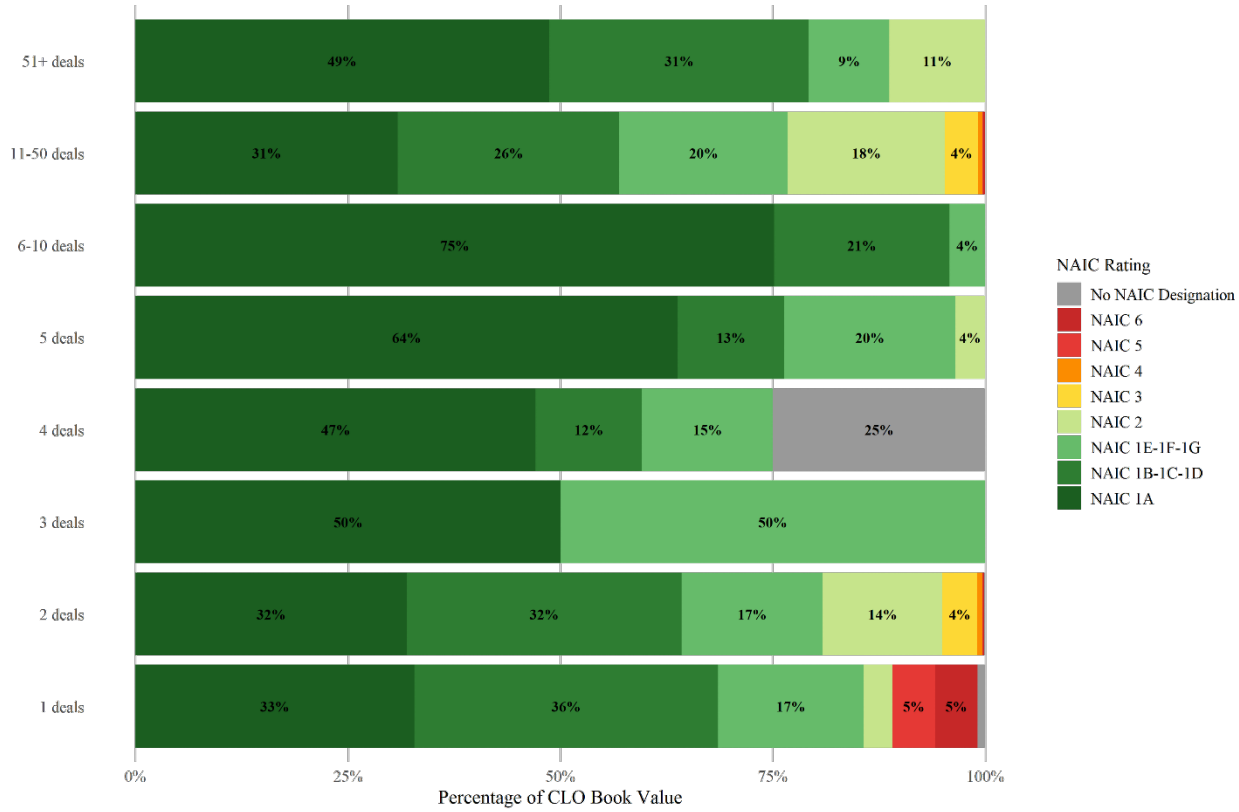


Figure 26 - Distribution of CLO Credit Quality, by Number of CLOs Owned



7.3 Proposed CLO PAF

The Academy proposes using the median relative PAF (by number of unique CLO deals owned) to avoid skew from small, seasoned CLOs. The Academy also proposes a factor of 1 for all insurers owning more than 10 unique CLO deals, due to the fast convergence of relative CLO PAF and the observed levels of diversification in the industry. Furthermore, the Academy recommends departing from the tiered bracket system used in the bond model; factors quickly change by number of CLOs owned and do not gradually decline like bond factors.

Proposed factors are:

Table 21 - Proposed CLO Portfolio Adjustment Factors (PAFs) by Number of Unique CLOs Owned

# of Unique CLOs	**Proposed Portfolio Adjustment Factor**
1	**1.3907**
2	**1.2222**
3	**1.1586**
4	**1.1254**
5	**1.1060**
6	**1.0926**
7	**1.0831**
8	**1.0760**
9	**1.0704**
10	**1.0661**
11+	**1.0000**

Alternatively, the Academy proposes a factor of 1.0 for all insurers, regardless of number of CLOs owned.

As detailed in Appendix N, more than half of insurers who hold 10 or fewer unique CLO deals are invested in Aa3 and above credit (specifically, 35 out of 56 insurers). For those insurers, implementation of the proposed PAFs would impact factors by *at most* 0.3907 × 0.04% = 0.015%. Among the insurers who invest in credit below Aa3, those who own three or fewer unique CLOs allocate no more than 0.9% of assets to CLOs. Those owning six or fewer allocate no more than 1.3% of total assets to CLOs. Those owning 7–10 CLOs allocate no more than 2.2% of total assets to CLOs, with the exception of one company that allocates 8.4% to CLOs.

The one outlier insurer owns three 2A CLOs, four thick 2C CLOs and two thin 2C CLOs. This averages out to a proposed base factor of 4.22%. The impact of PAF would be an increase of 0.0704 × 4.22% = 0.30%. In dollar amount, the PAF would increase the company's C-1o requirement by only 0.4% of total capital and surplus.

According to the first of the six guiding principles (see Section 3.1), "changes that have a small impact on RBC ratios may not justify a change to the RBC formula." For the vast majority of companies, the impact of the proposed PAF is either negligible or non-existent. For an outlier company, the impact is only 0.4% of capital and surplus. Given the relatively small impact of the proposal, the Academy concludes that the added complexity brought on by implementing PAF by number of issuers may not be justified.

8 Reconciliation of Proposed Model with Current C-1 Factors

The Academy performs an attribution analysis from the underlying loan losses to the weighted average C-1 Factors under the current and the proposed methodology. This section seeks to demonstrate that the

factors resulting from this model do not allow for RBC arbitrage[24].

8.1 Analyzing Collateral RBC, Collateral PV of Losses and Proposed CLO RBC

The Academy begins by comparing loans' current bond C-1 Factors (Collateral RBC shown below) to the modeled collateral present value of CTE90 losses (CLO Collateral Losses). For each CLO, the Academy looks through to the underlying loans and assigns a bond RBC by the loan rating. A weighted average is taken to get the RBC for the full portfolio of loans (by their balance within the CLO). Separately, the Academy looks at the 17 tail scenarios produced for CDOnet and assigns present value losses to all the underlying loans, utilizing the Riemann sum method to estimate CTE90 for the losses on those same loans.

Note that current bond factors are derived from VaR96 but the present value of collateral losses is CTE90. As shown in Appendix B, CTE90 is a roughly unbiased estimate of VaR96 in the bond model, so this discrepancy should not contribute much error.

In Figure 27, the difference between the collateral's RBC and CTE90 present value of losses is close to 0. The mean is 0.18% and median is -0.09%. This corroborates the Academy's implementation of the ACLI/MA Bond Model; there is no risk added or subtracted. For transparency, it should be noted that RBC includes losses on future reinvestments while the CTE90 PV losses apply only to original collateral. However, RBC also includes a risk premium that reduces the C-1 Factor below the present value of losses. These two discrepancies roughly offset one another.

Figure 27 - Collateral Bond Model RBC minus PV Original Collateral Loss CTE90

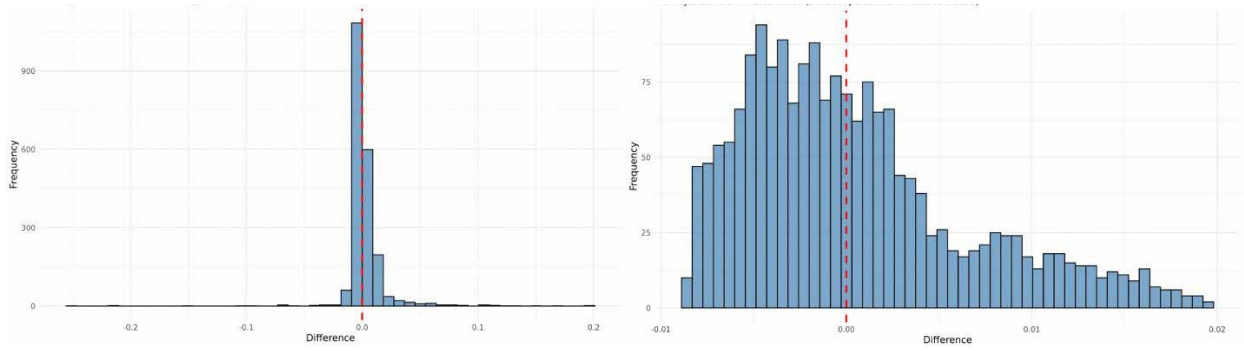
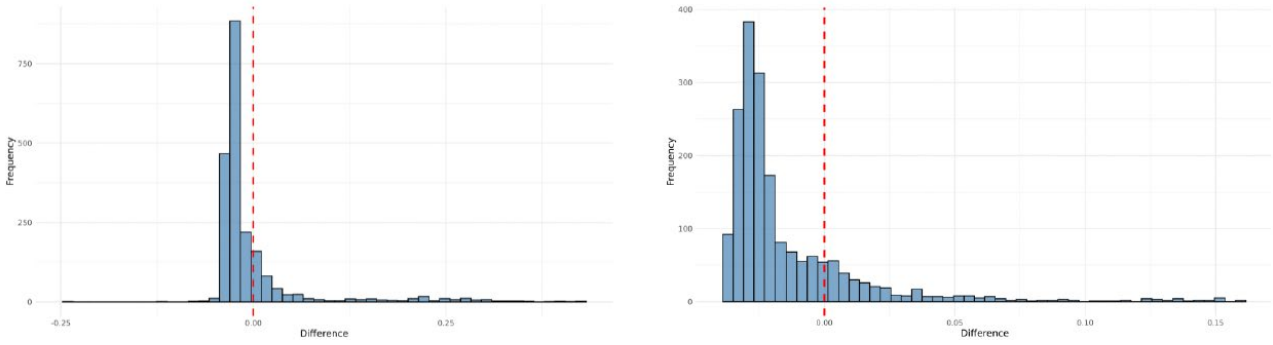


Figure 28 - PV Original Collateral Loss CTE90 minus Proposed CLO RBC (Face Value-Weighted)



The Academy concludes that there is no credit risk lost in the transition from bond factors to loan

[24] Here, RBC arbitrage is defined as a difference in capital required to hold a vertical slice of a CLO vs. holding its underlying collateral.

collateral losses. The Academy proceeds to evaluate the transition from collateral loss to proposed factors. For each CLO, the Academy applies the proposed factors to each tranche and averages the tranches together to estimate the CLO's vertical slice RBC.

In practice, CLO vertical slice RBC is derived by weighting the tranche RBC factors in proportion to *book value* since C-1 is calculated as a ratio of book value. But for this analysis, the Academy weights by *face value.* The reason for this is that the underlying loans are all assumed to be priced at par (both in the ACLI/MA Bond Model and in the Collateral Model), but CLO residual tranche accounting requires book value to dip below net asset value when income is received. This means that the total book value of the CLO vertical slice will almost always be less than the total book value of the underlying loans.

When the residual tranche's book value declines, the C-1 requirement for the security decreases in total dollar amount and the CLO's total RBC factor decreases. However, this decrease is not RBC arbitrage. If the residual tranche has less book value, it contributes less to TAC. This means that an insurance company owning the vertical slice CLO will report less asset value than an insurer owning all the underlying loans priced at par, despite owning an economically equivalent position.

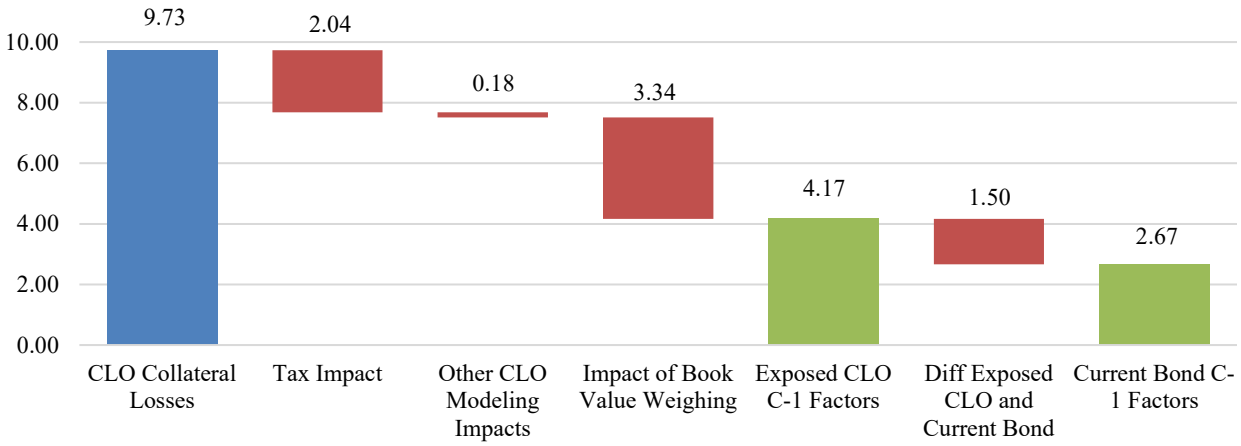
To make the calculations apples-to-apples, the Academy weights all the CLO tranches by face value in Figure 28 so that the CLO vertical slice has the same asset value as the underlying loans. The difference between the present value of original collateral losses at CTE90 and the vertical slice CLO RBC factors (also CTE90) averages -0.18% across all CLOs with a median of -2.44%. This indicates that *on average* the residual tranche accounting explains the gap between losses on collateral and final RBC factors. The skew in the median is further analyzed in Section 8.3.

8.2 Attribution Analysis from Collateral to Proposed CLO C-1 Factors

An attribution analysis is performed across the collateral and CLO deal universes, demonstrating that tax adjustments and residual tranche book value accounting explain the difference between the Final C-1 CLO Factors and the collateral losses modeled.

- CLO Collateral CTE90 Losses = PV of Pre-Tax Losses/Loan Balance as of 12/31/24 for CTE90 scenario
- Proposed CLO C-1 Factors on Vertical Slice = BV-weighted Proposed CLO C-1 Factors applied to the vertical slice of CLO deals based on the CLO tranche rating
- Current Bond C-1 Factors = BV-weighted Current C-1 Factors applied to the vertical slice of CLO deals based on the CLO tranche rating
- Tax Impact = CLO Collateral CTE90 Losses × 21%
- Impact of Book Value Weighting = Proposed CLO C-1 Factors – Face Value-Weighted Proposed C-1 Factors applied to the vertical slice of CLO deals based on the CLO tranche rating

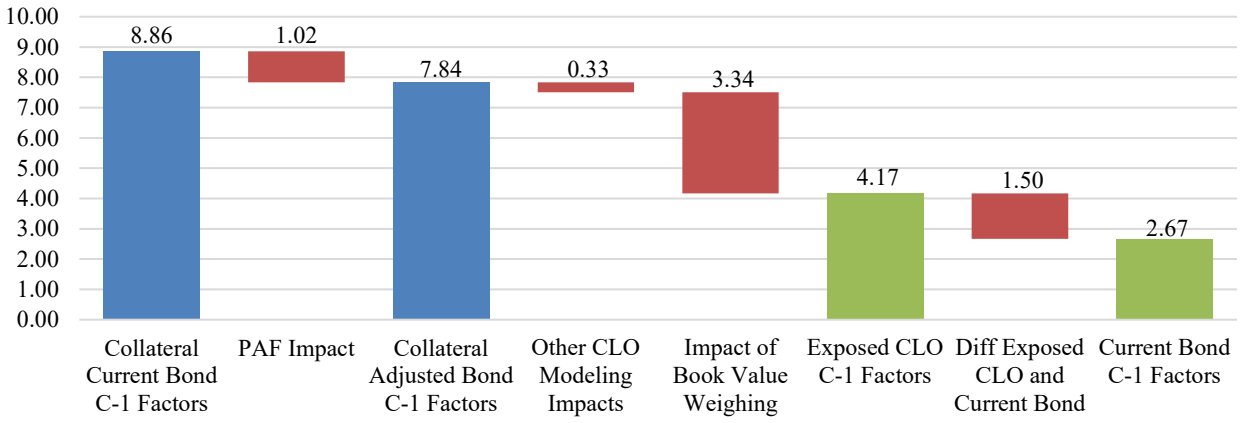
Figure 29 - Collateral Losses vs. Proposed C-1 Factors Attribution Analysis



The attribution analysis can be performed from the Current C-1 Factors applied to the collateral universe instead. The analysis demonstrates that diversification, represented by PAF, and residual tranche book value accounting explain the difference between the Final C-1 CLO Factors and the Current C-1 Factors.

- Collateral Base Current C-1 Factors = The base Current C-1 Bond Factors assigned by collateral issuer rating
- Collateral Adjusted Current C-1 Factors = Collateral Base Current C-1 Factors × PAF of 88.46%, estimated based on a total of 1,957 issuers in the collateral universe

Figure 30 - Current C-1 of Collateral vs. Proposed C-1 of CLO Vertical Slice Attribution Analysis



The Academy observes that the difference between the Current C-1 Factors, in particular the Bond Factors, and the Proposed CLO C-1 Factors is mostly explained by diversification (via PAF) and book value accounting of residual tranches. When comparing against the underlying collateral losses, the Proposed CLO C-1 Factors more accurately capture the risk at the CLO tranche level compared to the Current C-1 Factors.

8.3 Illustration of CLO with Median Collateral Loss

An example CLO deal is chosen because its collateral has the median loss PV across all deals. It is explored in detail, shown for the VaR96 loss scenario. As demonstrated in Appendix B, the VaR96 scenario is used as a proxy for CTE90. The Current Bond Factors are calibrated to VaR96.

Table 22 - Detailed Attribution Analysis Calculation for Median Loss Example CLO Deal

Illustrative Numbers from VaR96 for Specific Deal at Median Loss									
Tranche Rating	DP (%)	Thickness (%)	FV ($mn)	BV ($mn)	Pre-Tax Loss Undisc. ($mn)	Post-Tax Loss PV ($mn)	Post-Tax Loss PV (% FV)	BV PV Loss ($mn)	Post-Tax BV PV Loss (% BV)
			A	B	C	D	D ÷ A	E	E ÷ B
Aaa	100	63.8	410	410	0	0	0	0	0
Aa2	36.2	12.2	78	78	0	0	0	0	0
A2	24	7.1	46	46	0	0	0	0	0
Baa3	17	6.1	39	39	0	0	0	0	0
Ba3	10.9	3.8	24	24	22	14	56.87	14	56.87
NR	7.1	7.1	52	14	52	33	62.32	0	0
Total			**649**	**610**	**74**	**46**	**7.13**	**14**	**2.23**

In this example, the underlying collateral suffers $74mn of default (see column C). The face value of the residual tranche is $52mn and the face value of the Ba3 tranche is $24mn (i.e., $76mn total), so this loss fully penetrates the residual tranche and penetrates a majority of the Ba3 tranche. The losses do not occur until two years from the model date, so there are two years in which no impairment is recorded. The loss is lowered to $46mn when accounting for taxes and discounting. This accounts for 7.13% of the CLO's face value.

As illustrated in the prior section, CLO RBC factors are lowered by residual tranche accounting. In column B, it is shown that the residual tranche's starting book value is $14mn, which means $38mn of interest was received before Dec. 31, 2024, and used to pay down book value, under practical expedient accounting. In Section 8.2, it was demonstrated that the gap in initial face value and book value *on average* explains most of the gap between Bond RBC Factors (on the underlying collateral) and CLO Proposed Factors (on the vertical slices).

However, Figure 28 illustrated that this discrepancy only explains the gap on average; it does not explain the gap for the median CLO. If this CLO lost $14mn on the Ba3 tranche and $14mn on the residual tranche (the initial book value), the C-1 would be $28mn / $610mn = 4.59%. What is not considered is the interest paid to the residual tranche during the two years before impairment, for these exemplary cash flows. In that time, the residual tranche receives a hair over $14mn in interest which reduces the book value to $0. The final loss on the CLO is then $14mn and the loss as a proportion of book value is 2.23%.

In Table 23, it is shown that the collateral's average bond factor is 7.72% while the proposed CLO factor for the vertical slice is 2.34%, only 0.11% away from the VaR96 CLO book value loss. The gap is fully explained by the discrepancy in initial book/face value for the residual tranche *and* the change in book value from present to time of impairment.

Table 23 - Attribution Analysis for Median Loss Example CLO Deal

Statistics for Specific Deal at Median Loss	
CLO Collateral CTE90 Loss PV (% of Face Value "FV" = Book Value "BV")	7.47%
CLO Collateral Base Current C-1 Bond Factors (% of FV = BV)	7.72%
CLO Vertical Slice Post-Tax VaR96 ***Face Value*** Loss PV (% of total FV)	7.13%
CLO Vertical Slice Post-Tax VaR96 ***Book Value*** Loss PV (% of total BV)	2.23%
Proposed CLO C-1 Factors on Vertical Slice	2.34%
Current C-1 Factors on Vertical Slice	1.31%

Although the difference in residual book value accounting reduces the Proposed C-1 Factors for residual tranches, in the context of the overall U.S. RBC framework, TAC would have been reduced by the same book value accounting principles. The lower C-1 and lower TAC offset such that a life insurer that would reach its Company Action Level by holding the loans directly would also reach its Company Action Level by holding a CLO vertical slice.

Table 24 - Residual Tranche BV / FV[25]

BV / FV	
Average	35.02%
Standard Deviation	30.63%
10th Percentile	0.00%
25th Percentile	2.37%
Median	31.65%
75th Percentile	56.47%
90th Percentile	83.69%

Here the Academy also offers an intuitive explanation through a stylized example, using only approximate numbers, alongside the precise empirical work shown above. A typical CLO contains a portfolio of loans that would require an approximately 8% weighted average C-1 if the loans were held directly by a life insurer. In other words, C-1 requires that the insurer demonstrate its ability to withstand an 8% reduction in book value. If an insurer instead owns a vertical slice of a CLO containing this same loan portfolio, the C-1 under the factors proposed herein would be only 4%. But residual tranche accounting will likely have caused the residual tranche to have reduced its book value by an amount equal to 4% of the total vertical slice: the residual tranche accounts for roughly 8% of CLO face value and close to half of the 8% is written off in book value. The C-1 of 4% plus the amount of book value already written off, also 4%, equals the same 8% C-1 requirement the insurer would have been required to hold had it owned the loans directly.

9 Limitations and Areas for Future Work

The CLO market has gone through a few significant restructurings. If CLO structures evolve significantly again, the C-1 Factors presented here might become stale.

Market evolution notwithstanding, the CLO C-1 Modeling Framework represents a significant methodological advancement in the regulatory capital of CLO investments held by life insurers. The model involves a number of simplifying assumptions, data constraints, and open methodological questions that the Academy acknowledges as limitations. This section synthesizes those limitations and identifies specific

[25] Face value equals net asset value.

areas where future research or refinement could improve the framework.

9.1 Scope and Data

9.1.1 Data and Ratings Coverage

The collateral file used to characterize CLO pools contains rating gaps that introduce uncertainty into the loan-level default rate assignments. Approximately 87.7% of collateral line items carry an issuer-level rating from either Moody's or S&P, and 95.1% carry at least one rating at the security or issuer level. The remaining unrated exposures require a rating assignment based on available proxies, and any misclassification at the loan level propagates into the scenario-level default vectors passed to CDOnet. Future iterations of the model would benefit from improved data sourcing to reduce unrated exposure counts.

Additionally, approximately 28.6% of line items with ratings from both Moody's and S&P carry disagreeing ratings across the two agencies, with the lower rating assigned as a conservative measure. A future enhancement would be to revise the approach to derive a single final rating when there are differing ratings across agencies.

9.1.2 Middle Market CLOs

The current model is calibrated exclusively to broadly syndicated loan (BSL) CLOs. Middle market CLOs—which are collateralized by loans to smaller, less liquid borrowers—are not included in the sample and are not explicitly addressed by the framework. Middle market loans typically exhibit different default and recovery characteristics than broadly syndicated loans, including higher concentration risk, lower secondary market liquidity and potentially different recovery dynamics. A separate model calibration for middle market CLOs, or an explicit adjustment to the BSL-derived factors, may be appropriate before extending the framework to that asset class.

9.2 Credit Loss Assumptions

9.2.1 Recovery Rate Methodology

Recovery rate assumptions differ systematically between S&P and Moody's methodologies. Moody's measures recovery using trading prices 30 days after default, while S&P measures ultimate recovery; the current model uses S&P ultimate recovery data because S&P provides a probability distribution in deciles, while Moody's only provides an average. The ACLI/MA Bond Model uses a distribution of recoveries by decile, so the S&P data allows for better alignment with the ACLI/MA Bond Model. However, trading prices would better represent the experience of CLOs, since CLOs typically sell defaulted loans prior to resolution. A future enhancement would be to develop a more formal reconciliation of the two agencies' recovery data sets and assess whether a blended or agency-specific approach better reflects the economic reality of CLO collateral.

9.2.2 Recovery Rate Assumptions

The current model uses S&P decile recovery data for senior secured and unsecured loans. Several limitations attach to this approach. First, the recovery data does not distinguish between junior secured loans and mezzanine instruments, which may experience materially different recovery outcomes than senior secured loans. A more granular segmentation of recovery distributions by seniority tier—including junior secured and unsecured categories—would improve the precision of loss modeling at the collateral level.

Second, secular trends in loan recovery rates driven by the widespread adoption of covenant-lite (cov-lite) loan structures are not explicitly modeled. Cov-lite agreements reduce lender protections and may compress recoveries in future default cycles relative to historical averages. The current model implicitly assumes the historical S&P recovery distribution is representative of future recoveries, which may be overly optimistic in a structurally weaker credit environment.

Third, recovery rates for senior and non-senior tranches of the same issuer are sampled independently in the simulation, which can produce the theoretically inconsistent outcome of a subordinated tranche recovering more than a senior tranche in a given scenario. This arises from the absence of a joint probability mass function governing the two recovery rates simultaneously. Should S&P (or Moody's) provide joint recovery distributions in the future, incorporating a correlated sampling approach would eliminate this inconsistency.

9.2.3 Default Rate Assumptions for Below-Investment-Grade Issuers

The default rates applied to Ba1/below-rated issuers in the Collateral Model are derived from the ACLI/MA Bond Model. There is an open question as to whether these rates are overly conservative when applied to leveraged loans, given the structural protections and active management embedded in CLO vehicles. The ACLI/MA Bond Model was designed to focus on IG public unsecured credit, while the collateral of CLOs is predominantly below-IG first-lien bank loans.

The low baseline IRRs for the residual tranche equity provide strong evidence that the default assumptions are overly punitive. Under the baseline run, the median IRR among new CLOs (no cash flows before Dec. 31, 2024) is 0%, indicating that the default rates may be unreasonable and not reflective of reality. Further investigation into loan-specific default rates for below-investment-grade issuers—distinct from bond-derived rates—could refine the Collateral Model and reduce potential conservatism at the lower end of the rating spectrum.

9.2.4 Modeling Correlation in Defaults

The Collateral Model applies a Gaussian copula with 10% pairwise default correlation, consistent with the ACLI/MA Bond Model, and this parameter is held constant for cross-model comparability. However, the Gaussian copula is a known limitation in structured credit modeling: it does not capture tail dependence, meaning it may understate the probability of simultaneous widespread defaults during systemic stress events. The Clayton copula sensitivity test demonstrated that alternative copula specifications can produce materially higher C-1 Factors for mezzanine and subordinated tranches, confirming that the copula choice is a consequential assumption. Alternative copula specifications should be reviewed when the ACLI/MA Bond Model assumptions and methodology are next modified.

9.2.5 Modeling Correlation in Recovery Rates

Similarly, the current Collateral Model does not capture correlation between recovery rates and default rates, nor the resulting correlation among recovery rates across issuers within the same scenario. In high-default environments, recoveries tend to be lower—both due to asset price depression and increased supply of distressed assets—meaning that treating recovery rates as independent of default severity understates tail losses. Sensitivity testing confirmed that introducing correlated severities produces notably higher C-1 Factors at mezzanine ratings. Incorporating a joint default-recovery correlation structure in future model iterations would improve the accuracy of tail loss estimation.

These limitations also apply to the ACLI/MA Bond Model. Should there be revisions to the bond model, it may be appropriate to revisit the correlation assumptions and stress test for transparency.

9.3 Reinvestment Assumptions and Methodology

9.3.1 Prepayment and Reinvestment Price Assumptions

The baseline assumptions in the CLO C-1 Modeling Framework assume no voluntary prepayment and reinvestment at par. Sensitivity analysis demonstrates that applying historically low prepayment speeds and discounted repurchase prices reduces C-1 Factors for certain tranches because prepayment activity under stress redistributes principal away from equity and toward rated tranches. Two sensitivities were tested. The first corresponds to the average of every observation less than or equal to the 10th percentile of the historical data of each of the prepayment speeds and purchase prices. The second corresponds to the VaR0.5 of the

same data. The net directional impact of these assumptions is therefore tranche-dependent and non-trivial, and the current approach of maintaining both at baseline is acknowledged as an expedient rather than a fully optimized choice. A future enhancement would model prepayment rates and reinvestment prices specifically calibrated to high-default tail environments, providing a more internally consistent stress scenario rather than applying separate sensitivity tests.

9.3.2 Reinvestment Methodology

The reinvestment methodology used in the Collateral Model (Method 4) assigns default rates to reinvested loans based on average simulated loss rates starting at time zero, rather than accounting for the credit migration of those loans between the reinvestment date and the end of the stress horizon. This introduces a ratings mismatch: a loan reinvested one or more years into the scenario is assigned risk based on default rates 1+ years out from rating (rather than default rates for newly rated loans). A transition-matrix approach (Method 5) was considered but not implemented due to concerns about false precision and the introduction of additional model assumptions. Revisiting this approach or developing a simplified migration adjustment remains an area for future enhancement.

The reinvestment credit quality distribution (30% B1, 30% B2, 40% B3) and seniority mix (92.5% senior secured, 7.5% non-senior secured) are hard-coded as representative of the new-issue CLO market and are not adjusted at the deal level. While a review of the sample deals confirmed these parameters are broadly reasonable, soft-coding these inputs at the deal or vintage level would improve accuracy. Similarly, the reinvestment horizon of 2.5 years and the assumption that reinvested assets carry maturities exceeding 10 years are fixed assumptions that may not reflect the characteristics of individual deals, particularly seasoned CLOs with shortened reinvestment periods.

Lastly, a generic set of reinvestment assumptions is hard-coded across all CLO deals in the Collateral Model. A future refinement would be to reflect the individual deal's reinvestment parameters in the Collateral Model.

9.4 CLO Deal and C-1 Factor Assumptions

9.4.1 Risk Premium

The risk premium was assumed to be equal to the premium used for bonds of equal agency rating, from the ACLI/MA Bond Model. This assumption was made to maintain consistency with the ACLI/MA Bond Model; no additional research was done to evaluate what risk premium reasonably represents the risk covered by conservatism in the reserving assumptions.

Furthermore, the ACLI/MA Bond Model assumes that the risk premium sits half a standard deviation above mean for a given rating's present value. Since the Academy only has access to 17 scenarios that are processed by CDOnet, it was not possible to estimate mean and standard deviation. The 70th percentile roughly matches half a standard deviation over mean. Despite running a 70th percentile scenario, the Academy found the results to be too noisy to be useful. Should further analysis be done with more scenarios passed through CDOnet, it would be appropriate to add scenarios in the neighborhood of the 70th percentile to better estimate what the risk premium should be for CLOs.

9.4.2 CLO Resets and Refinancings

CLO resets and refinancings are not addressed in the current CLO C-1 Modeling Framework. A reset materially changes a CLO's structural characteristics—including its reinvestment period, liability costs, and collateral profile—and could substantially affect the applicable C-1 Factor. The current approach effectively treats all CLOs as static structures as of the modeling date. Future work should assess how resets and refinancings interact with the factor table and whether a post-reset recalibration or separate factor category is warranted.

9.4.3 Seasoning

The question of whether and how to capture the seasoning of individual CLO deals—that is, the degree to which a CLO's reinvestment period, collateral vintage, and structural features have evolved since issuance—was identified early in the C-1 Subcommittee's deliberations as a material modeling consideration. No specific CDOnet input or model parameter currently addresses seasoning in a systematic way. As the framework matures, developing an explicit treatment for deal seasoning would improve the granularity and accuracy of factor assignments across the CLO universe.

9.5 Modeling Methodology

9.5.1 Bucketing of A3-Rated Tranches

The treatment of A3-rated tranches in the comparable attributes regression model is an open methodological question. A3 presents a persistent fitting challenge due to its compressed reinvestment horizon, limited data observations, and position at the boundary between two natural groupings. The tranche can plausibly be grouped with A2 (for statistical credibility) or with Baa1 (for structural similarity within the reinvestment interaction term). The two bucketing approaches tested (labeled "Proposed Buckets" and "Alternative Buckets") do not produce a decisive outcome, so simple averaging the two factors together was a subjective determination. Future refinement, particularly as additional data becomes available, should revisit these bucketing options with a larger sample.

9.5.2 Scenario Count

The CTE90 calculation is based on 17 tail scenarios drawn from 10,000 simulated scenarios generated by the Collateral Model. While 17 scenarios are sufficient to define CTE90 at a point estimate, a larger number of scenarios spanning the tail would reduce Monte Carlo estimation error and produce more stable factor estimates, particularly for tranches near the boundary of the stressed tail. Computational constraints limited the current implementation, and expanding the scenario count in future iterations would improve precision.

9.5.3 Isotonic Regression

A corollary model limitation is the use of isotonic regression. The regression does not help explain variation; it is a post hoc modeling decision that smooths out unintuitive results. Because there are so few non-zero C-1 Factors for A/above CLOs, the charges are subject to sampling error. If more stochastic simulations were run, it is possible that the average factors for A/above CLOs would monotonically increase as rating declines. There is no way to verify this due to the limited sample size and limited number of simulations.

9.5.4 Tranche Thickness Groupings

The Academy determined tranche thickness to be an important comparable attribute, but, for simplicity, created a binary flag for thickness greater than or less than 4%. Further subdivisions of thickness were not tested since the 4% cutoff appears sufficient for the data set analyzed. It is not necessarily the case that 4% would be an effective cutoff line in future iterations of this model, particularly should the market evolve and the typical CLO structures change.

Additionally, the 4% number was chosen heuristically rather than computationally. 4% was selected based on how it bifurcates Baa3 tranches but with little regard to lower-rated tranches that are less widely held by life insurers. This avoids false precision, but a different cutoff (like 4.25%) may better differentiate groups of risks. The Academy leaves this as an open debate, given that there are operational barriers to implementation. Adding tranche thickness as a comparable attribute in the RBC formula would require an amendment to the RBC templates.

9.5.5 Interaction Term Buckets

When regressing C-1 against reinvestment horizon, interaction terms are integral due to the non-linear increase of C-1 across ratings. However, as discussed, credibility issues preclude the Academy from regressing against a unique coefficient on reinvestment horizon for each rating. Doing so produces erratic results. To solve this, similar ratings must be bucketed together for the purpose of estimating the effect of reinvestment horizon on C-1. For most ratings, the choice of buckets does not materially impact the derived factors. But for A3, the factor radically changes when it is grouped with Baa1/Baa2 rather than A1/A2. There is no objective test to determine which grouping is "right." Accordingly, the Academy made a judgment call on this factor based on the data available. Should more A3 tranches exist in the future, this specific rating should be the subject of additional research.

9.5.6 Allowable Earned Yield C-1 Modeling

The IRRs used to estimate book yield introduce survivorship bias by implicitly assuming that the insurer rightly predicted the past interest payments. However, the survivorship bias slightly counteracts the even greater issue: the baseline projections produce residual tranche IRRs near 0%, particularly when focusing on newly issued securities. This issue causes the allowable earned yield C-1 Factors to closely approximate practical expedient factors. It prevents the Academy from doing a comprehensive analysis on how accounting method impacts risk (and whether the two accounting methods should have different C-1 Factors) and it prevents the Academy from evaluating the impact of assuming that residual tranches are only surplus-backing (the liability-backing accounting also approaches practical expedient accounting when book yield approaches 0%). To conduct such an analysis, the overall model would first have to be altered to remove its inherent conservatism. Specifically, residual tranche IRRs would need to be significantly higher than zero.

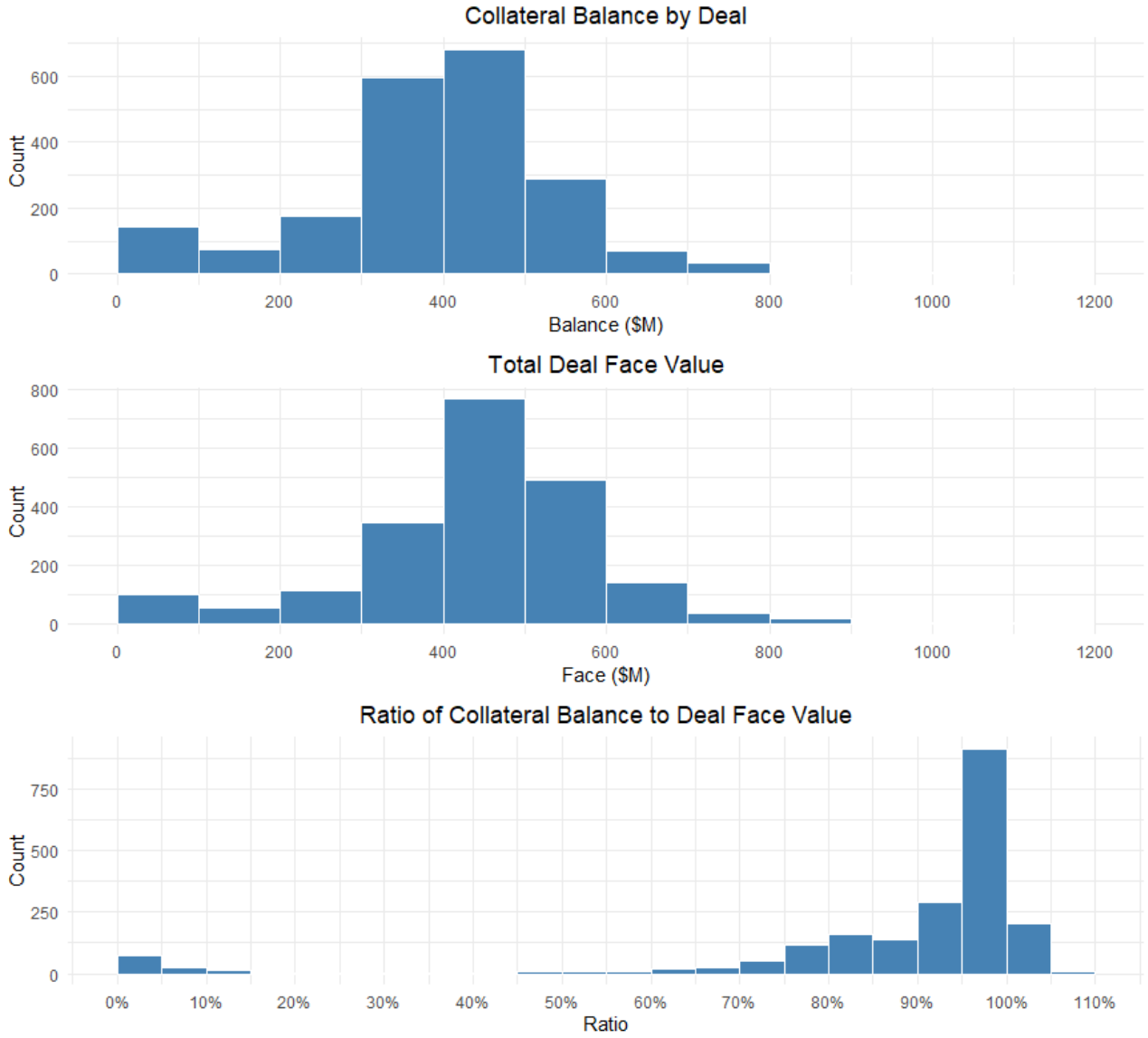
9.5.7 Residual Tranche Comparable Attributes

The Academy failed to identify sufficiently explanatory residual tranche comparable attributes. Certain variables, like debt credit quality, did have statistically significant predictive power, but the explanatory power was dwarfed by random noise in the C-1 Factors. It is unclear if the random noise is endemic to the product or if the noise is caused by model error and compounded in the residual tranche. The large dispersion within each tested risk bucket may also be driven by residual tranche accounting, where the book value relative to face value is sufficiently important to overpower other variables that more directly represent investment risk rather than statutory book value risk.

Future analysis would likely require more than 17 cash flow simulations to overcome the sampling noise. The analysis would also be improved if each CLO were modeled from issuance. The CLOs passed through CDOnet include those that began payments multiple years prior to the simulation start date. In such cases, the book value can be reduced down to (or close to) 0, which reduces the number of effective data points. Were the CLOs all modeled from issuance and C-1 Factors calculated by year, the residual tranche C-1 Factors could be regressed against the time-since-issuance to better isolate the intrinsic risk of the securities.

Appendix A Data Input Summary

Figure A.1 - Distribution of Collateral Balance



			Percentiles								
	Mean	**Std**	**1%**	**5%**	**10%**	**25%**	**50%**	**75%**	**90%**	**95%**	**99%**
Collateral Balance by Deal ($mn)	**419.0**	135.7	4.3	182.9	253.9	374.2	**404.7**	495.8	561.5	604.3	786.6
Total Deal Face Value ($mn)	**452.7**	129.9	107.6	252.8	313.2	400.2	**434.1**	508.7	604.9	651.1	834.1
Ratio (Collateral to Deal)	**90.9%**	15.0%	3.9%	68.9%	77.7%	88.1%	**96.0%**	98.5%	100.1%	101.4%	104.0%

Figure A.2 - Distribution of Unique Loans per CLO Deal

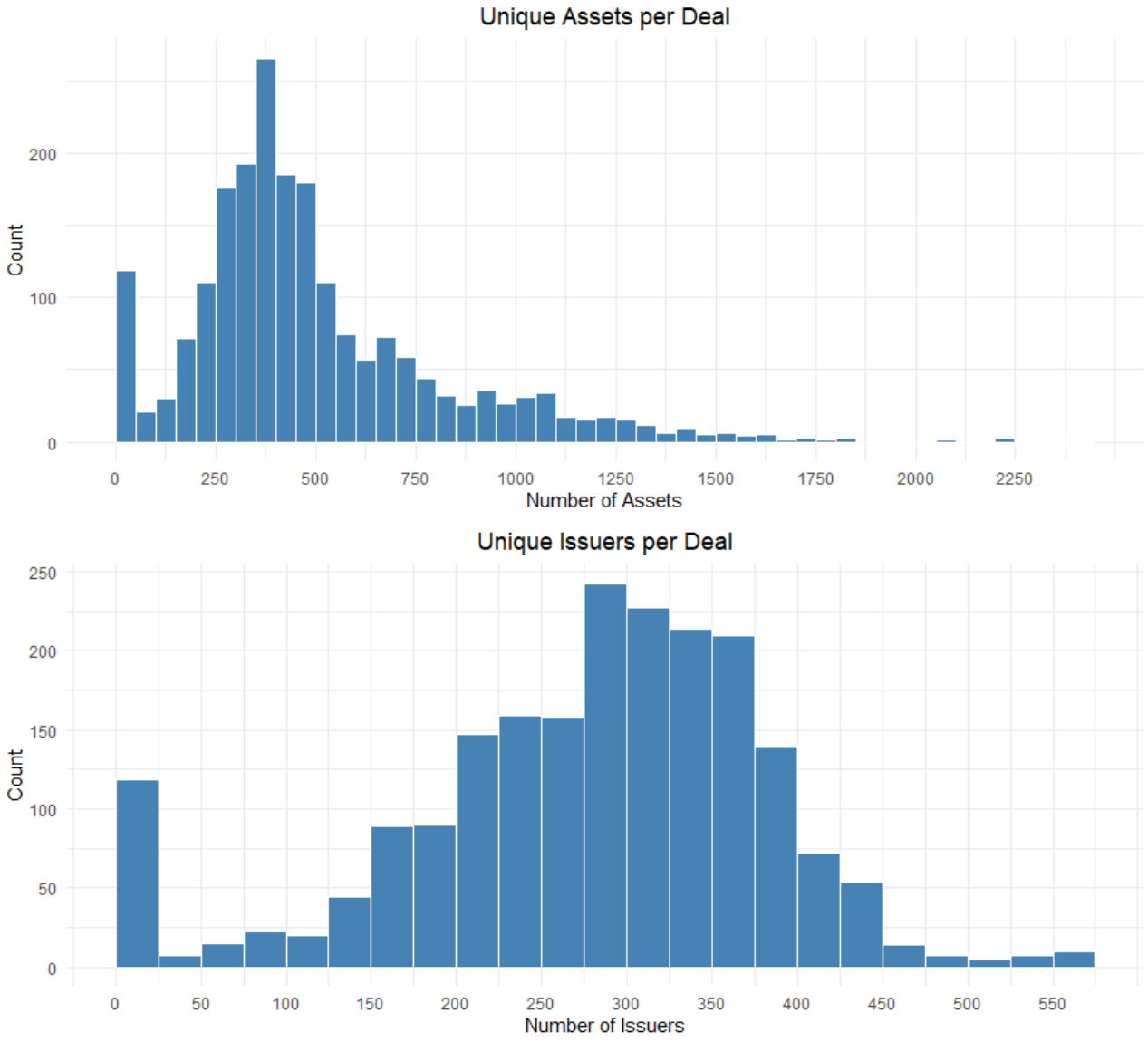
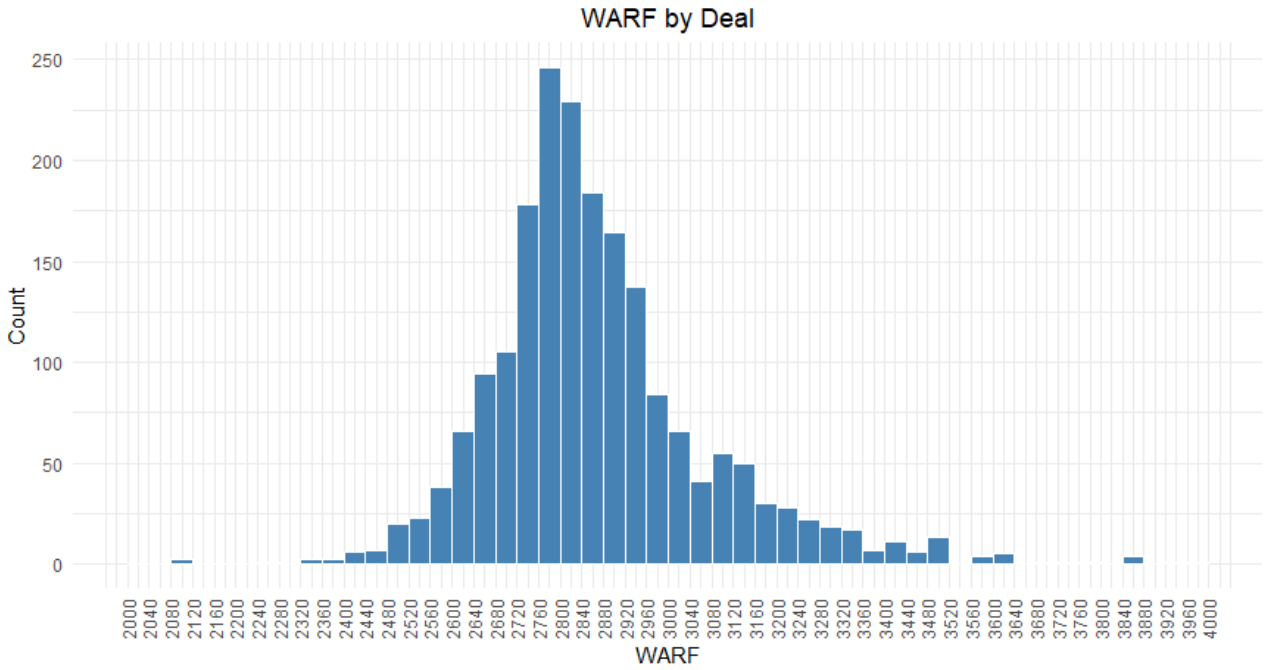


Figure A.3 - Distribution of WARF by CLO Deal



			Percentiles								
	Mean	Std	1%	5%	10%	25%	**50%**	75%	90%	95%	99%
WARF by Deal	**3,019**	745	2,483	2,600	2,660	2,755	**2,844**	2,979	3,254	3,948	7,003

Table A.1 - Missing Ratings in Collateral Data

			Percentiles								
	Mean	Std	1%	5%	10%	25%	**50%**	75%	90%	95%	99%
Unique Assets (total count)	**515**	312	9	174	235	318	**422**	631	977	1,175	1,532
Unique Issuers (total count)	**290**	93	5	132	171	233	**299**	355	394	425	510

	By Frequency		By Balance	
	Count	Proportion	Aggregate	Proportion
Moody's Issuer	268,273	21.5%	301,718,147,896	25.7%
S&P Issuer	222,727	17.9%	292,151,917,814	24.9%
Moody's Security	59,530	4.8%	111,744,952,079	9.5%
S&P Security	73,582	5.9%	129,844,442,522	11.0%
Fitch Security	632,984	50.8%	609,538,948,843	51.9%
Both Issuer Ratings	93,425	7.5%	144,059,707,568	12.3%
All 3 Security Ratings	28,732	2.3%	59,598,769,290	5.1%
All 5 Rating	27,624	2.2%	57,882,274,954	4.9%

Appendix B Stress Testing ACLI/MA Bond Model Parameters

CTE vs. VaR

The Academy adjusts the R script provided by Moody's Analytics so that base C-1 is estimated from conditional tail expectation (rather than value-at-risk). Comparing the published VaR96 to various CTEs (below), the Academy finds that CTE90 is the most neutral alternative.

Table B.1 - Estimated CTE and VaR96 from ACLI/MA Bond Model

	VaR	CTE										
	96	86	87	88	89	90	91	92	93	94	95	96
Aaa	0.16%	0.14%	0.15%	0.15%	0.16%	0.17%	0.18%	0.20%	0.21%	0.23%	0.25%	0.27%
Aa1	0.27%	0.23%	0.24%	0.26%	0.27%	0.28%	0.30%	0.31%	0.33%	0.36%	0.38%	0.42%
Aa2	0.42%	0.38%	0.39%	0.41%	0.43%	0.44%	0.46%	0.49%	0.51%	0.54%	0.58%	0.62%
Aa3	0.52%	0.48%	0.50%	0.52%	0.54%	0.57%	0.59%	0.62%	0.65%	0.69%	0.73%	0.79%
A1	0.66%	0.60%	0.62%	0.64%	0.67%	0.69%	0.72%	0.76%	0.80%	0.84%	0.89%	0.95%
A2	0.82%	0.72%	0.75%	0.78%	0.81%	0.84%	0.88%	0.92%	0.96%	1.02%	1.08%	1.16%
A3	1.02%	0.90%	0.93%	0.97%	1.01%	1.05%	1.09%	1.14%	1.20%	1.26%	1.34%	1.43%
Baa1	1.26%	1.11%	1.15%	1.19%	1.23%	1.28%	1.34%	1.40%	1.48%	1.56%	1.66%	1.79%
Baa2	1.52%	1.37%	1.41%	1.46%	1.51%	1.57%	1.63%	1.69%	1.77%	1.85%	1.95%	2.07%
Baa3	2.17%	1.95%	2.02%	2.09%	2.16%	2.24%	2.33%	2.43%	2.55%	2.68%	2.83%	3.02%
Ba1	3.15%	2.84%	2.93%	3.03%	3.13%	3.25%	3.37%	3.51%	3.66%	3.84%	4.05%	4.31%
Ba2	4.54%	4.18%	4.30%	4.43%	4.56%	4.71%	4.87%	5.05%	5.26%	5.49%	5.76%	6.10%
Ba3	6.02%	5.25%	5.40%	5.56%	5.73%	5.91%	6.12%	6.35%	6.61%	6.91%	7.27%	7.71%
B1	7.39%	6.63%	6.80%	6.99%	7.19%	7.40%	7.64%	7.90%	8.18%	8.51%	8.89%	9.36%
B2	9.54%	8.54%	8.75%	8.98%	9.22%	9.48%	9.78%	10.09%	10.45%	10.86%	11.34%	11.93%
B3	12.43%	11.27%	11.52%	11.79%	12.08%	12.39%	12.74%	13.12%	13.56%	14.08%	14.67%	15.38%
Caa1	16.94%	15.35%	15.63%	15.94%	16.27%	16.62%	17.01%	17.45%	17.93%	18.48%	19.11%	19.90%
Caa2	23.80%	22.18%	22.55%	22.95%	23.38%	23.84%	24.35%	24.89%	25.50%	26.20%	27.01%	28.02%
Caa3	32.98%	31.07%	31.49%	31.94%	32.41%	32.92%	33.49%	34.12%	34.80%	35.57%	36.44%	37.47%

Table B.2 - Estimated CTE vs. VaR96 from ACLI/MA Bond Model

	CTE – VaR96										
	86	87	88	89	90	91	92	93	94	95	96
Aaa	-0.02%	-0.01%	0.00%	0.00%	0.01%	0.03%	0.04%	0.05%	0.07%	0.09%	0.12%
Aa1	-0.04%	-0.03%	-0.02%	0.00%	0.01%	0.03%	0.04%	0.06%	0.09%	0.11%	0.15%
Aa2	-0.04%	-0.02%	-0.01%	0.01%	0.03%	0.05%	0.07%	0.09%	0.12%	0.16%	0.21%
Aa3	-0.04%	-0.02%	0.00%	0.02%	0.04%	0.07%	0.10%	0.13%	0.17%	0.21%	0.26%
A1	-0.06%	-0.04%	-0.02%	0.01%	0.04%	0.07%	0.10%	0.14%	0.18%	0.24%	0.30%
A2	-0.09%	-0.07%	-0.04%	-0.01%	0.03%	0.06%	0.10%	0.15%	0.20%	0.27%	0.35%
A3	-0.11%	-0.08%	-0.05%	-0.01%	0.03%	0.07%	0.13%	0.18%	0.25%	0.32%	0.42%
Baa1	-0.15%	-0.11%	-0.07%	-0.03%	0.02%	0.08%	0.14%	0.21%	0.30%	0.40%	0.53%
Baa2	-0.16%	-0.11%	-0.06%	-0.01%	0.04%	0.10%	0.17%	0.25%	0.33%	0.43%	0.55%
Baa3	-0.21%	-0.15%	-0.08%	-0.01%	0.08%	0.16%	0.27%	0.38%	0.51%	0.66%	0.85%
Ba1	-0.31%	-0.22%	-0.12%	-0.02%	0.10%	0.22%	0.36%	0.51%	0.69%	0.90%	1.16%
Ba2	-0.36%	-0.24%	-0.11%	0.03%	0.17%	0.34%	0.52%	0.72%	0.95%	1.22%	1.56%
Ba3	-0.77%	-0.62%	-0.46%	-0.29%	-0.10%	0.10%	0.33%	0.59%	0.89%	1.25%	1.70%
B1	-0.76%	-0.58%	-0.40%	-0.20%	0.02%	0.25%	0.51%	0.79%	1.12%	1.51%	1.98%
B2	-0.99%	-0.78%	-0.56%	-0.32%	-0.05%	0.24%	0.56%	0.92%	1.32%	1.80%	2.39%
B3	-1.16%	-0.91%	-0.64%	-0.35%	-0.03%	0.31%	0.70%	1.14%	1.65%	2.24%	2.95%
Caa1	-1.60%	-1.31%	-1.00%	-0.67%	-0.32%	0.07%	0.51%	0.99%	1.53%	2.17%	2.96%
Caa2	-1.62%	-1.25%	-0.85%	-0.42%	0.04%	0.55%	1.09%	1.70%	2.40%	3.22%	4.22%
Caa3	-1.91%	-1.48%	-1.04%	-0.56%	-0.05%	0.52%	1.14%	1.83%	2.60%	3.46%	4.49%
RMSE	0.82%	0.64%	0.45%	0.26%	0.10%	0.23%	0.49%	0.78%	1.11%	1.50%	1.97%

Including/Excluding Economic States

When re-running the R script provided by Moody's Analytics *without* the economic states (i.e., assuming the economic state is always expanding), the resulting C-1 Factors are on average roughly unchanged.

Table B.3 - Economic States Stress Test from ACLI/MA Bond Model

	With Econ States	Without Econ States	Difference
Aaa	0.16%	0.16%	0.00%
Aa1	0.27%	0.26%	-0.01%
Aa2	0.42%	0.43%	0.01%
Aa3	0.52%	0.55%	0.02%
A1	0.66%	0.68%	0.02%
A2	0.82%	0.80%	-0.02%
A3	1.02%	1.00%	-0.01%
Baa1	1.26%	1.22%	-0.04%
Baa2	1.52%	1.53%	0.01%
Baa3	2.17%	2.19%	0.02%
Ba1	3.15%	3.16%	0.01%
Ba2	4.54%	4.68%	0.14%
Ba3	6.02%	5.73%	-0.29%
B1	7.39%	7.32%	-0.07%
B2	9.54%	9.40%	-0.14%
B3	12.43%	12.23%	-0.19%
Caa1	16.94%	16.38%	-0.56%
Caa2	23.80%	23.58%	-0.22%
Caa3	32.98%	32.90%	-0.08%

Comparing Gaussian Copula Correlations

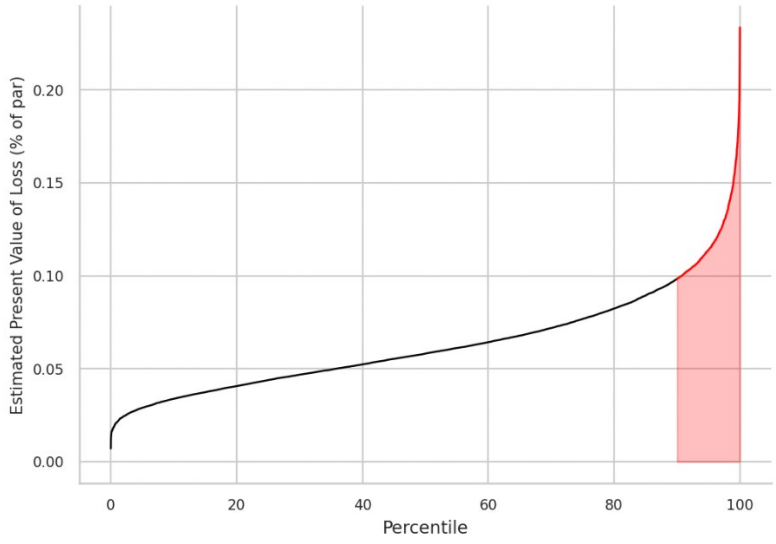
The ACLI/MA Bond Model assumes 10% correlation in the Gaussian copula. Re-running the code provided by Moody's Analytics with alternate correlation assumptions yields a wide range of C-1 Factors.

Table B.4 - Correlation Stress Test from ACLI/MA Bond Model

	Adopted	Gaussian-Copula Correlation:				Difference			
	C-1 Factors	0%	5%	20%	40%	0%	5%	20%	40%
Aaa	0.16%	0.15%	0.15%	0.16%	0.18%	-0.01%	-0.01%	0.00%	0.02%
Aa1	0.27%	0.24%	0.26%	0.31%	0.37%	-0.03%	-0.01%	0.04%	0.10%
Aa2	0.42%	0.37%	0.41%	0.54%	0.81%	-0.05%	-0.01%	0.12%	0.39%
Aa3	0.52%	0.42%	0.48%	0.69%	0.98%	-0.10%	-0.04%	0.16%	0.46%
A1	0.66%	0.50%	0.59%	0.90%	1.52%	-0.16%	-0.07%	0.24%	0.86%
A2	0.82%	0.58%	0.68%	1.15%	2.16%	-0.23%	-0.13%	0.33%	1.35%
A3	1.02%	0.66%	0.80%	1.50%	2.64%	-0.36%	-0.22%	0.49%	1.62%
Baa1	1.26%	0.75%	0.96%	1.86%	3.35%	-0.51%	-0.30%	0.60%	2.09%
Baa2	1.52%	0.88%	1.19%	2.40%	4.32%	-0.65%	-0.33%	0.88%	2.80%
Baa3	2.17%	1.10%	1.60%	3.47%	6.11%	-1.07%	-0.57%	1.30%	3.94%
Ba1	3.15%	1.41%	2.24%	4.96%	9.32%	-1.74%	-0.91%	1.81%	6.17%
Ba2	4.54%	1.86%	3.33%	7.39%	13.09%	-2.67%	-1.20%	2.86%	8.56%
Ba3	6.02%	2.21%	4.10%	8.81%	15.59%	-3.81%	-1.91%	2.79%	9.58%
B1	7.39%	2.78%	5.32%	11.23%	18.99%	-4.61%	-2.07%	3.84%	11.60%
B2	9.54%	3.47%	6.94%	14.19%	23.55%	-6.06%	-2.60%	4.65%	14.01%
B3	12.43%	5.00%	9.05%	17.50%	28.04%	-7.43%	-3.38%	5.07%	15.62%
Caa1	16.94%	7.56%	13.04%	23.50%	34.82%	-9.38%	-3.91%	6.55%	17.88%
Caa2	23.80%	11.86%	18.95%	30.62%	43.70%	-11.94%	-4.85%	6.82%	19.90%
Caa3	32.98%	18.80%	27.46%	42.33%	55.81%	-14.18%	-5.51%	9.36%	22.84%

Appendix C Scenario Weights

Figure C.1 - Illustrative CTE90

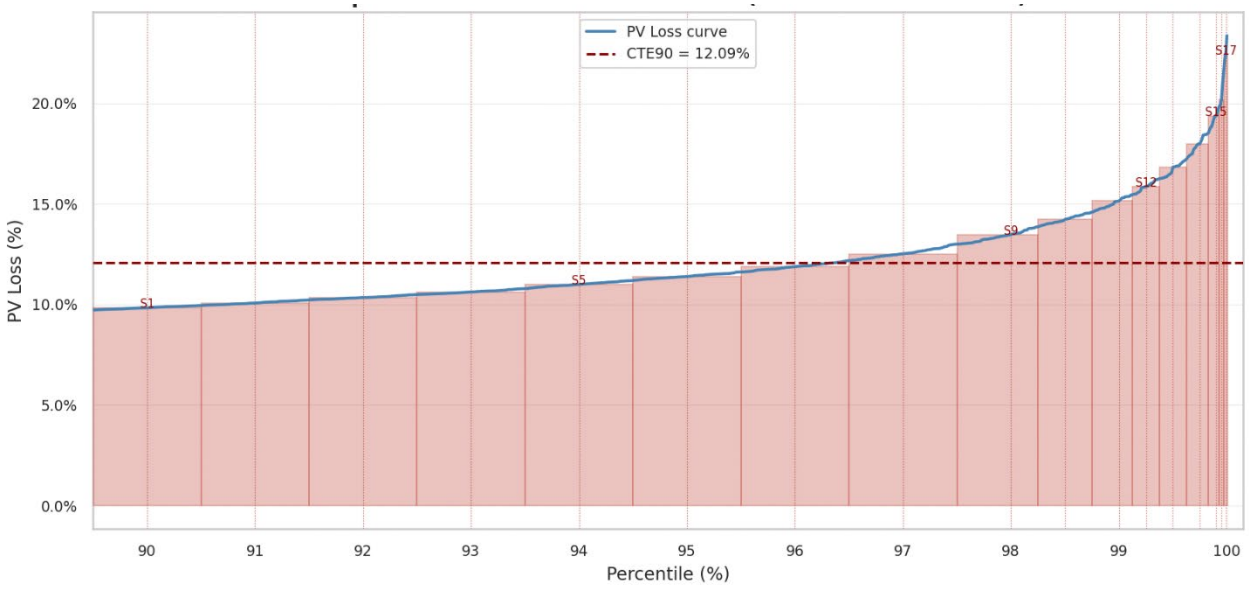


The Academy models 18 scenarios. The 70th percentile is run as a reference for researching risk premium; the other 17 are run to model the tail risk. Because the tail losses increase at an increasing rate, the percentiles become more granular the farther right they get. The Midpoint Riemann Sum method is used to approximate the CTE. The weights are as follows:

Table C.1 - Percentile Scenario Weights for CTE90

Scenario #	Percentile	Weight
1	90.00	5.00%
2	91.00	10.00%
3	92.00	10.00%
4	93.00	10.00%
5	94.00	10.00%
6	95.00	10.00%
7	96.00	10.00%
8	97.00	10.00%
9	98.00	7.50%
10	98.50	5.00%
11	99.00	3.75%
12	99.25	2.50%
13	99.50	2.50%
14	99.75	2.00%
15	99.90	1.00%
16	99.95	0.45%
17	99.99	0.30%
18	*70.00*	*0.00%*

Figure C.2 - Midpoint Riemann Sum for CTE90



Appendix D Illustrative CLO Debt Cash Flows to Raw C-1 Factors

The following table (split into two parts) presents fields for a Baa3 CLO bond. The TR_COUPON has been transformed to a monthly interest rate. The maximum present value of deficiency (post-tax) occurs at month (PERIOD) 15 with a value of 17,343,422. This is 57.85% of original balance, so the C-1 Factor is 57.85%.

Table D.1 - Illustrative C-1 Factor Calculation for a Baa3 CLO Bond (Part 1)

	BALANCE	INTEREST	PRIN	LOSSES	INT_DUE	INT_DEFERRED	TR_COUPON	TOTAL_CF	INNER_LOOP_PV	PRE_IMPAIRMENT_BV	IMPAIRMENT_FLAG	IMPAIRMENT
0	30,000,000	0	0	0	0	0	0.00%	0	10,217,245	30,000,000	0	0
3	30,000,000	0	0	0	0	0	0.64%	0	10,409,684	30,582,112	0	0
6	30,000,000	1,330,291	0	0	1,330,291	0	0.64%	1,330,291	9,275,458	29,845,229	0	0
9	30,000,000	565,331	0	0	565,331	0	0.62%	565,331	8,884,073	29,852,535	0	0
12	30,000,000	565,331	0	0	565,331	0	0.62%	565,331	8,485,348	29,847,038	0	0
15	30,571,543	0	0	0	571,543	571,543	0.62%	0	8,644,476	30,406,768	1	21,762,292
18	31,141,313	0	0	0	569,770	1,141,313	0.62%	0	8,806,589	8,806,589	1	0
21	31,728,151	0	0	0	586,838	1,728,151	0.62%	0	8,971,741	8,971,741	1	0
24	32,332,618	0	0	0	604,467	2,332,618	0.62%	0	9,139,991	9,139,991	1	0
27	32,948,601	0	0	0	615,983	2,948,601	0.62%	0	9,311,396	9,311,396	1	0
30	33,562,673	0	0	0	614,072	3,562,673	0.62%	0	9,486,015	9,486,015	1	0
33	34,195,140	0	0	0	632,467	4,195,140	0.62%	0	9,663,909	9,663,909	1	0
36	34,846,607	0	0	0	651,467	4,846,607	0.62%	0	9,845,140	9,845,140	1	0
39	35,510,485	0	0	0	663,878	5,510,485	0.62%	0	10,029,768	10,029,768	1	0
42	36,179,657	0	0	0	669,172	6,179,657	0.62%	0	10,217,860	10,217,860	1	0
45	36,861,439	0	0	0	681,782	6,861,439	0.62%	0	10,409,478	10,409,478	1	0
48	37,563,703	0	0	0	702,263	7,563,703	0.62%	0	10,604,690	10,604,690	1	0
51	38,294,902	0	0	0	731,200	8,294,902	0.62%	0	10,803,563	10,803,563	1	0
54	38,992,755	0	0	0	697,852	8,992,755	0.62%	0	11,006,166	11,006,166	1	0
57	39,727,548	0	0	0	734,793	9,727,548	0.62%	0	11,212,567	11,212,567	1	0
60	40,500,869	0	0	0	773,320	10,500,869	0.62%	0	11,422,840	11,422,840	1	0
63	41,272,468	0	0	0	771,600	11,272,468	0.62%	0	11,637,056	11,637,056	1	0
66	42,041,675	0	0	0	769,206	12,041,675	0.62%	0	11,855,289	11,855,289	1	0
69	42,833,923	0	0	0	792,248	12,833,923	0.62%	0	12,077,615	12,077,615	1	0
72	43,641,101	0	0	0	807,178	13,641,101	0.62%	0	12,304,110	12,304,110	1	0
75	44,472,526	0	0	0	831,426	14,472,526	0.62%	0	12,534,853	12,534,853	1	0
78	45,301,373	0	0	0	828,847	15,301,373	0.62%	0	12,769,922	12,769,922	1	0
81	46,155,048	0	0	0	853,675	16,155,048	0.62%	0	13,009,401	13,009,401	1	0
84	47,024,810	0	0	0	869,762	17,024,810	0.62%	0	13,253,370	13,253,370	1	0
87	47,920,701	0	0	0	895,890	17,920,701	0.62%	0	13,501,914	13,501,914	1	0
90	48,823,735	0	0	0	903,035	18,823,735	0.62%	0	13,755,120	13,755,120	1	0
93	49,743,787	0	0	0	920,052	19,743,787	0.62%	0	14,013,073	14,013,073	1	0
96	50,691,478	0	0	0	947,691	20,691,478	0.62%	0	14,275,865	14,275,865	1	0
99	51,657,223	0	0	0	965,745	21,657,223	0.62%	0	14,543,584	14,543,584	1	0
102	52,619,973	0	0	0	962,750	22,619,973	0.62%	0	14,816,324	14,816,324	1	0
105	53,611,563	0	0	0	991,589	23,611,563	0.62%	0	15,094,179	15,094,179	1	0
108	54,632,940	0	0	0	1,021,377	24,632,940	0.62%	0	15,377,245	15,377,245	1	0
111	0	1,040,836	14,624,783	40,008,157	1,040,836	10,008,157	0.62%	15,665,619	0	0	1	0

Table D.2 - Illustrative C-1 Factor Calculation for a Baa3 CLO Bond (Part 2)

	POST_IMPAIRMENT_BV	RISK_PREMIUM	PV_ACCUM_DEFICIENCY	TAX_BASIS	UNREALIZED_TAX_LOSS	REALIZED_TAX_LOSS	DTA_CHANGE	PV_ACCUM_DEFICIENCY_TAX_ADJ
0	30,000,000	0	0	30,000,000	0	0	0	0
3	30,582,112	-9,226	-27,342	30,000,000	-582,112	0	32,807	69,974
6	29,845,229	-9,003	-54,579	30,000,000	154,771	0	-190,045	-79,235
9	29,852,535	-9,006	-81,145	30,000,000	147,465	0	-63,425	-104,510
12	29,847,038	-9,004	-107,478	30,000,000	152,962	0	-63,431	-131,710
15	8,644,476	-2,608	20,712,379	30,571,543	21,927,067	0	-3,720,545	17,343,422
18	8,806,589	-2,657	20,704,838	31,141,313	22,334,725	0	-86,587	17,270,132
21	8,971,741	-2,706	20,697,221	31,728,151	22,756,410	0	-89,283	17,194,954
24	9,139,991	-2,757	20,689,529	32,332,618	23,192,627	0	-92,070	17,117,836
27	9,311,396	-2,809	20,681,760	32,948,601	23,637,205	0	-93,827	17,039,778
30	9,486,015	-2,862	20,673,913	33,562,673	24,076,658	0	-93,325	16,962,912
33	9,663,909	-2,915	20,665,989	34,195,140	24,531,231	0	-96,231	16,884,066
36	9,845,140	-2,970	20,657,985	34,846,607	25,001,467	0	-99,235	16,803,185
39	10,029,768	-3,026	20,649,901	35,510,485	25,480,716	0	-101,128	16,721,320
42	10,217,860	-3,082	20,641,737	36,179,657	25,961,797	0	-101,823	16,639,580
45	10,409,478	-3,140	20,633,492	36,861,439	26,451,961	0	-103,742	16,556,867
48	10,604,690	-3,199	20,625,164	37,563,703	26,959,012	0	-106,981	16,472,018
51	10,803,563	-3,259	20,616,754	38,294,902	27,491,339	0	-111,636	16,383,810
54	11,006,166	-3,320	20,608,259	38,992,755	27,986,589	0	-105,823	16,301,551
57	11,212,567	-3,382	20,599,680	39,727,548	28,514,981	0	-111,815	16,214,802
60	11,422,840	-3,446	20,591,016	40,500,869	29,078,029	0	-118,070	16,123,403
63	11,637,056	-3,511	20,582,265	41,272,468	29,635,412	0	-117,558	16,033,286
66	11,855,289	-3,576	20,573,427	42,041,675	30,186,386	0	-116,930	15,944,542
69	12,077,615	-3,643	20,564,500	42,833,923	30,756,308	0	-120,570	15,853,515
72	12,304,110	-3,712	20,555,485	43,641,101	31,336,991	0	-122,843	15,761,402
75	12,534,853	-3,781	20,546,380	44,472,526	31,937,674	0	-126,678	15,666,912
78	12,769,922	-3,852	20,537,184	45,301,373	32,531,451	0	-126,001	15,573,862
81	13,009,401	-3,925	20,527,897	46,155,048	33,145,648	0	-129,924	15,478,418
84	13,253,370	-3,998	20,518,517	47,024,810	33,771,441	0	-132,373	15,381,835
87	13,501,914	-4,073	20,509,044	47,920,701	34,418,786	0	-136,505	15,282,761
90	13,755,120	-4,149	20,499,476	48,823,735	35,068,616	0	-137,442	15,183,838
93	14,013,073	-4,227	20,489,812	49,743,787	35,730,714	0	-140,034	15,083,736
96	14,275,865	-4,307	20,480,053	50,691,478	36,415,613	0	-144,404	14,981,052
99	14,543,584	-4,387	20,470,196	51,657,223	37,113,639	0	-147,160	14,877,117
102	14,816,324	-4,470	20,460,241	52,619,973	37,803,649	0	-146,374	14,774,766
105	15,094,179	-4,553	20,450,187	53,611,563	38,517,383	0	-150,931	14,669,780
108	15,377,245	-4,639	20,440,032	54,632,940	39,255,695	0	-155,641	14,562,086
111	0	0	20,433,206	0	0	-6,721,370	6,562,759	14,456,749

Appendix E Risk Premium Comparison

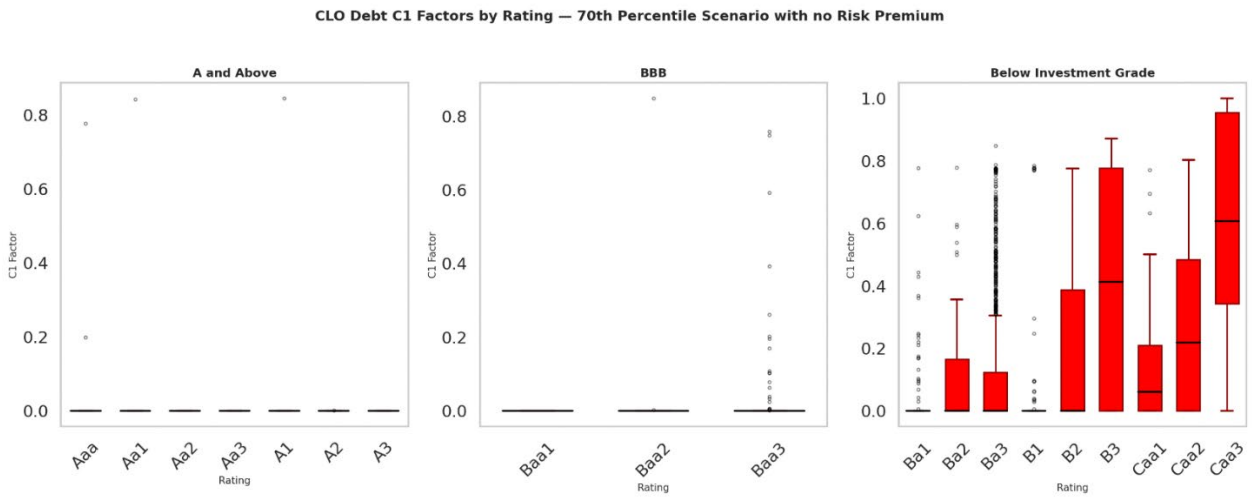
In the ACLI/MA Bond Model, the risk premium is assigned by rating and is estimated as half a standard deviation above the mean present value of losses. For a standard normal distribution, the 69.15th percentile is one-half of a standard deviation above the mean. Therefore, the Academy considers the 70th percentile. After calculating the 70th percentile C-1 (assuming a risk premium of 0), the Academy observes erratic results; contrary to expectation, the factors do not strictly increase as credit quality declines.

Table E.1 - Comparison of VaR70 ACLI/MA Bond Model vs. Collateral Model

Rating	Risk Premium		Difference
	ACLI/MA Bond Model	70th Percentile of CLOs	
Aaa	0.007%	0.026%	0.019%
Aa1	0.015%	0.284%	0.269%
Aa2	0.032%	0.000%	-0.032%
Aa3	0.046%	0.000%	-0.046%
A1	0.065%	0.343%	0.278%
A2	0.092%	0.000%	-0.092%
A3	0.123%	0.000%	-0.123%
Baa1	0.168%	0.000%	-0.168%
Baa2	0.229%	0.239%	0.010%
Baa3	0.362%	0.197%	-0.165%
Ba1	0.579%	4.527%	3.948%
Ba2	0.932%	10.119%	9.187%
Ba3	1.225%	9.709%	8.484%
B1	1.619%	4.240%	2.621%
B2	2.168%	20.487%	18.319%
B3	2.834%	39.888%	37.054%
Caa1	3.787%	14.195%	10.408%
Caa2	5.274%	28.978%	23.704%
Caa3	7.998%	58.960%	50.962%

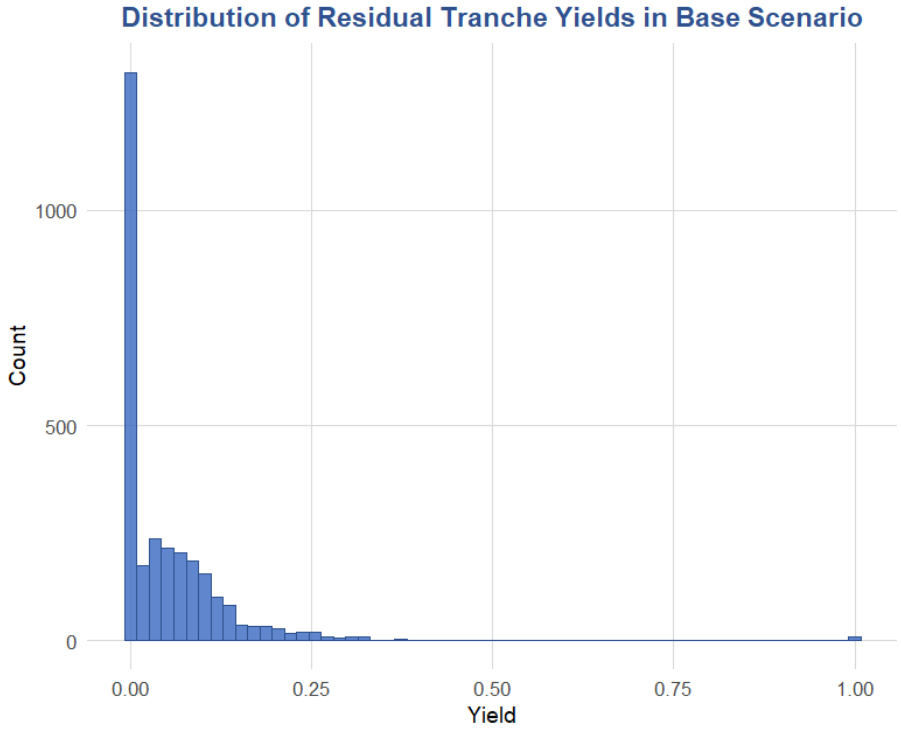
Additionally, the box plot reveals that for investment-grade bonds, the 70th percentile factors would be 0 but for outlier results. This means any risk premium derived from the 70th percentile will be predominantly relying on outliers rather than on clusters around a mean.

Figure E.1 - CLO Debt Raw C-1 Factors at VaR70 by Rating

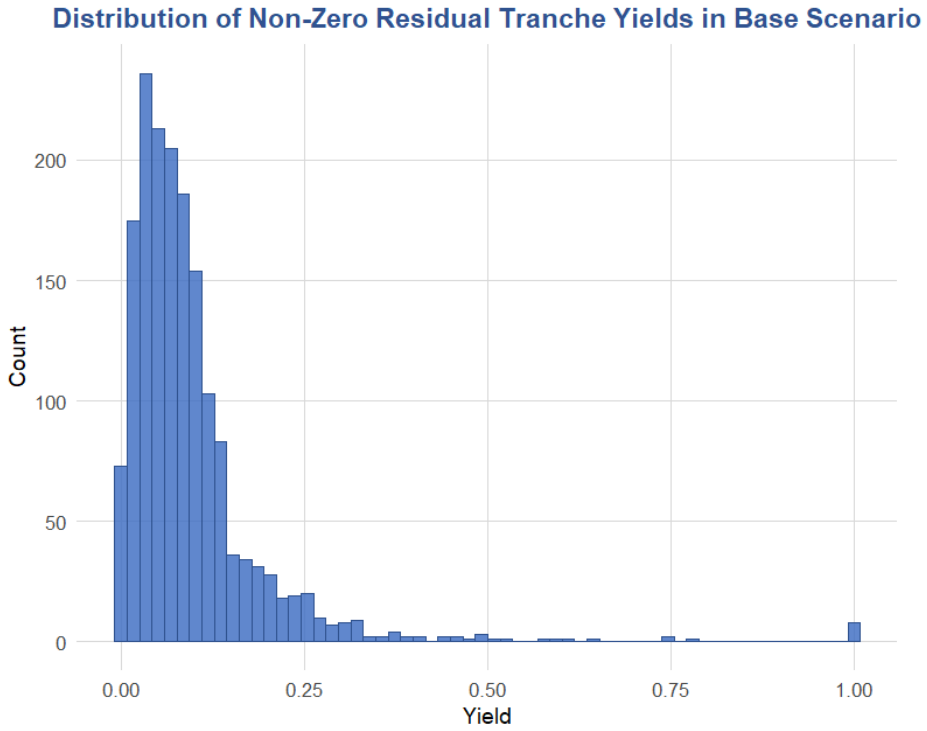


Appendix F Mean Scenario Residual Tranche IRRs

When running the baseline "mean scenario" projections, the Academy runs CDOnet with the mean default rates per year by credit rating and the mean recovery rates. The residual tranche IRRs are calculated from the net cash flows (principal + interest) from first contribution to last distribution, capping at 0% and 100%. The Academy observes that 42.55% of residual tranches have a 0% IRR under the mean scenario.



Statistic	Value
Mean	0.0542
Standard Deviation	0.0914
5th Percentile	0.0000
10th Percentile	0.0000
25th Percentile	0.0000
50th Percentile	0.0229
75th Percentile	0.0804
90th Percentile	0.1358
95th Percentile	0.1986



Statistic	Value
Mean	0.0943
Standard Deviation	0.1037
5th Percentile	0.0095
10th Percentile	0.0187
25th Percentile	0.0379
50th Percentile	0.0706
75th Percentile	0.1128
90th Percentile	0.1877
95th Percentile	0.2495

Appendix G Tested Regressions for Comparable Attributes

The Academy's baseline for comparable attributes is ratings-only. The following regressions were run against other comparable attributes. These include (but are not limited to):

a) Attachment and detachment points (AP and DP respectively; "tranche thickness" is derived as the difference between DP and AP)
b) Interest coverage and overcollateralization (tests, ratios and levels)
c) Flags for the levels of subordination (senior, mezzanine, junior)
d) Current and initial balance of the CLO tranche (ratios of current-to-original and current tranche-to-current deal are derived)
e) Number of years until the end of reinvestment and until the formal maturity
f) The coupon rate
g) Collateral credit quality (WARF and the proportion in each rating)
h) Collateral weighted average time to maturity
i) Total balance and number of unique issuers and assets within the collateral

The Academy observes that when running simple OLS and without transforming any variable, ratings explain more variance than all other attributes. The Academy does observe that attachment and detachment points are explanatory when divided up into sufficiently many buckets (e.g., 1–2%, 2–3%, etc.).

Table G.1 - Tested Regressions for Potential Comparable Attributes

Regression Exogenous Variables	Adj R^2	# of Parameters	Notes
All Variables, excluding Rating (no transformations)	42.64%	47	Baseline estimate for non-rating characteristics
AP Percentile Buckets (50 equal-sized)	66.54%	50	
Tranche Thickness Percentile Buckets (50 equal-sized)	45.29%	50	
DP Percentile Buckets (50 equal-sized)	76.47%	50	New baseline for non-rating characteristics. Downside: agnostic towards underlying credit quality.
Rating	74.22%	19	Baseline for ratings. Explanatory power comparable to detachment point
Rating + DP	74.42%	20	Adds little additional explanatory power over rating
Rating + DP Buckets	81.82%	68	Explains an additional 7.6% of variance over ratings only
Rating + Reinv Horizon	76.23%	20	Reinvestment horizon explains an additional 2.0% of variance over ratings only; is the most explanatory variable when added to rating (w/o transformation)
Rating + Reinv Horizon x Rating (interaction terms with rating)	82.42%	37	Explains an additional 8.2% of variance over ratings only; potential overfitting on thin tranches
Rating + Reinv Horizon x Rating Letter (interactions with AAA, AA, A, etc.)	81.58%	26	Loses less than 1% of variance explained Adds credibility to non-standard tranches
Rating + Reinv Horizon x Rating Bucket (interactions with B3/below, B2/B1/Ba3, Baa3/Ba1/Ba2, etc.)	81.63%	26	Comparable R^2 as rating letter; adds credibility to CCC (adds observations and adds variance in horizon)
Rating + Reinv Horizon x Rating Bucket + Tranche Coupon	82.34%	27	Minor improvement over model without tranche coupon
Rating + Reinv Horizon x Rating Bucket + DP	81.72%	27	Negligible improvement over model without DP
Rating + Reinv Horizon x Rating Bucket + DP	85.63%	75	Detachment point (at the granular level) explains an additional 4.0% of variance
Rating + Reinv Horizon x Rating Bucket + Thickness	81.66%	27	Negligible improvement over model without thickness
Rating + Reinv Horizon x Rating Bucket + Flag for [Thickness ≤ 4% & Baa3/below Rating]	83.25%	27	Explains additional 1.6% of variance over model without thickness or DP; chosen model
Rating + Reinv Horizon x Rating Bucket + Flag for [Thickness ≤ 4% & Baa3/below Rating] + Tranche Coupon	83.71%	28	Explains only 0.5% additional variance Without tranche thickness, coupon added 0.75%; this suggests that coupon rate is a proxy
Rating + Reinv Horizon x Rating Bucket + Flag for [Thickness ≤ 4% & Baa3/below Rating] * Rating	84.34%	36	Explains only 1% additional variance with 9 additional variables; potential overfitting for below-IG
Rating + Reinv Horizon x Rating Bucket + Flag for [Thickness ≤ 4% & Baa3/below Rating] + DP Buckets	85.70%	76	Reference point: granular detachment point data only explains an additional 2.5% of variance over chosen model

Appendix H Tranche Thickness Kernel Density

Kernel density estimation (KDE) is a non-parametric technique for estimating the probability density function of a continuous random variable without imposing a parametric distributional assumption. Given a sample of n observed thickness values $x_1, x_2, \ldots, x_n$, the KDE estimator evaluates the density at any point x as

$$\hat{f}(x) = \frac{1}{nh} \times \sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right)$$

where h is the bandwidth and K is the Gaussian kernel function, where $K(u) = \frac{1}{\sqrt{2\pi}} \times e^{-\frac{u^2}{2}}$. The density is evaluated on a fine grid of n = 2,048 equally spaced points spanning the support of the data, producing a smooth continuous approximation of the empirical thickness distribution. The bandwidth is selected using Silverman's Rule of Thumb, which minimizes the mean integrated squared error (MISE) under the assumption that the true density is Gaussian: $h = 0.9 \times \min\left(\hat{\sigma}, \frac{IQR}{1.34}\right) \times n^{-\frac{1}{5}}$, $\hat{\sigma}$ is the sample standard deviation and IQR is the interquartile range. Because tranche thickness distributions are typically multimodal and right-skewed (Silverman's rule tends to over-smooth in such cases), the bandwidth is further scaled by a factor of 0.4 to sharpen the resolution of distinct thickness clusters. This multiplier was selected through visual inspection of the resulting density estimates across rating tiers and can be tuned as needed.

The densities of thickness for each Baa1 and below rating are in the figures below.

Figure H.1 - Kernel Density Estimation for Tranche Thickness (Baa1 through Ba1)

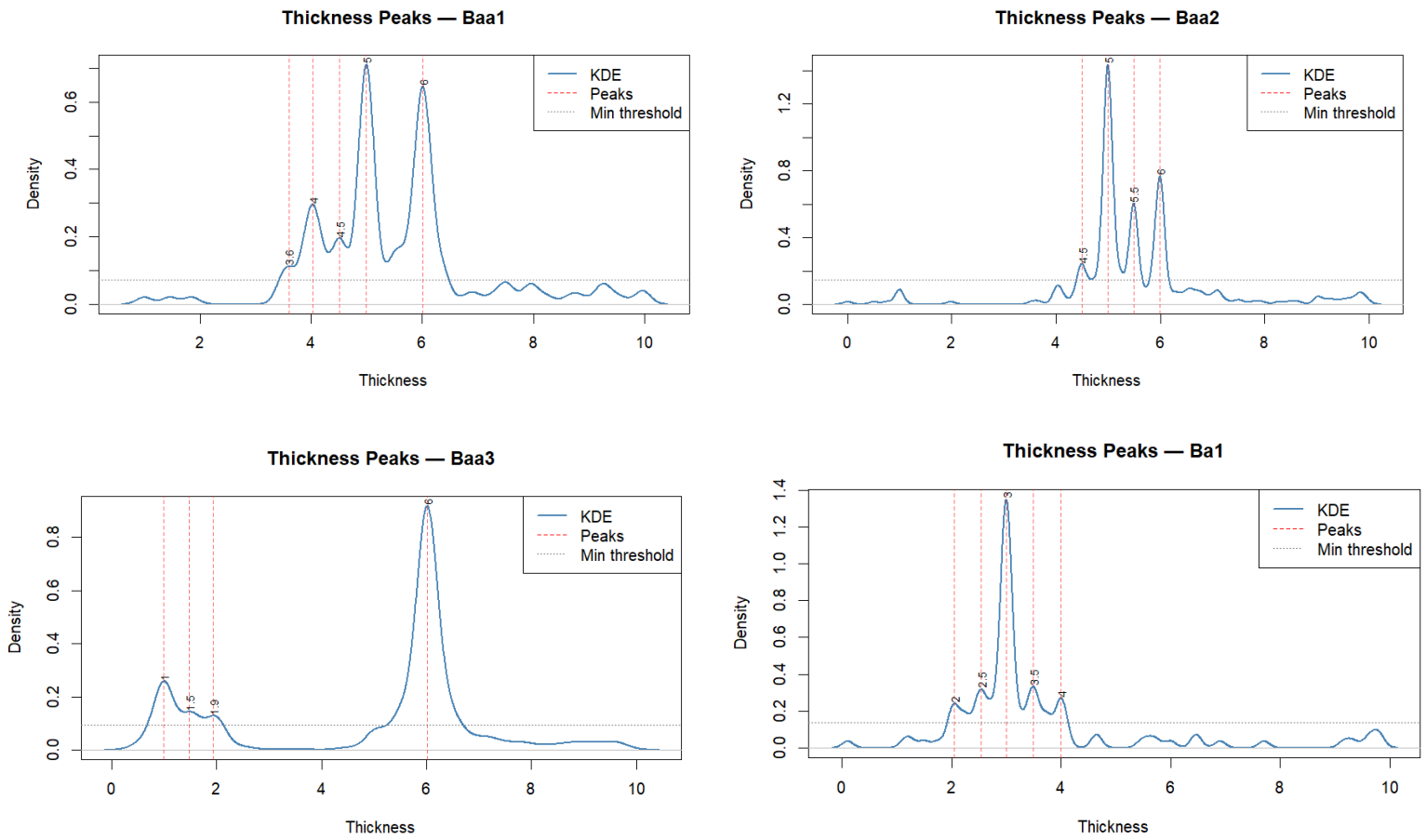


Figure H.2 - Kernel Density Estimation for Tranche Thickness (Ba2 through B2)

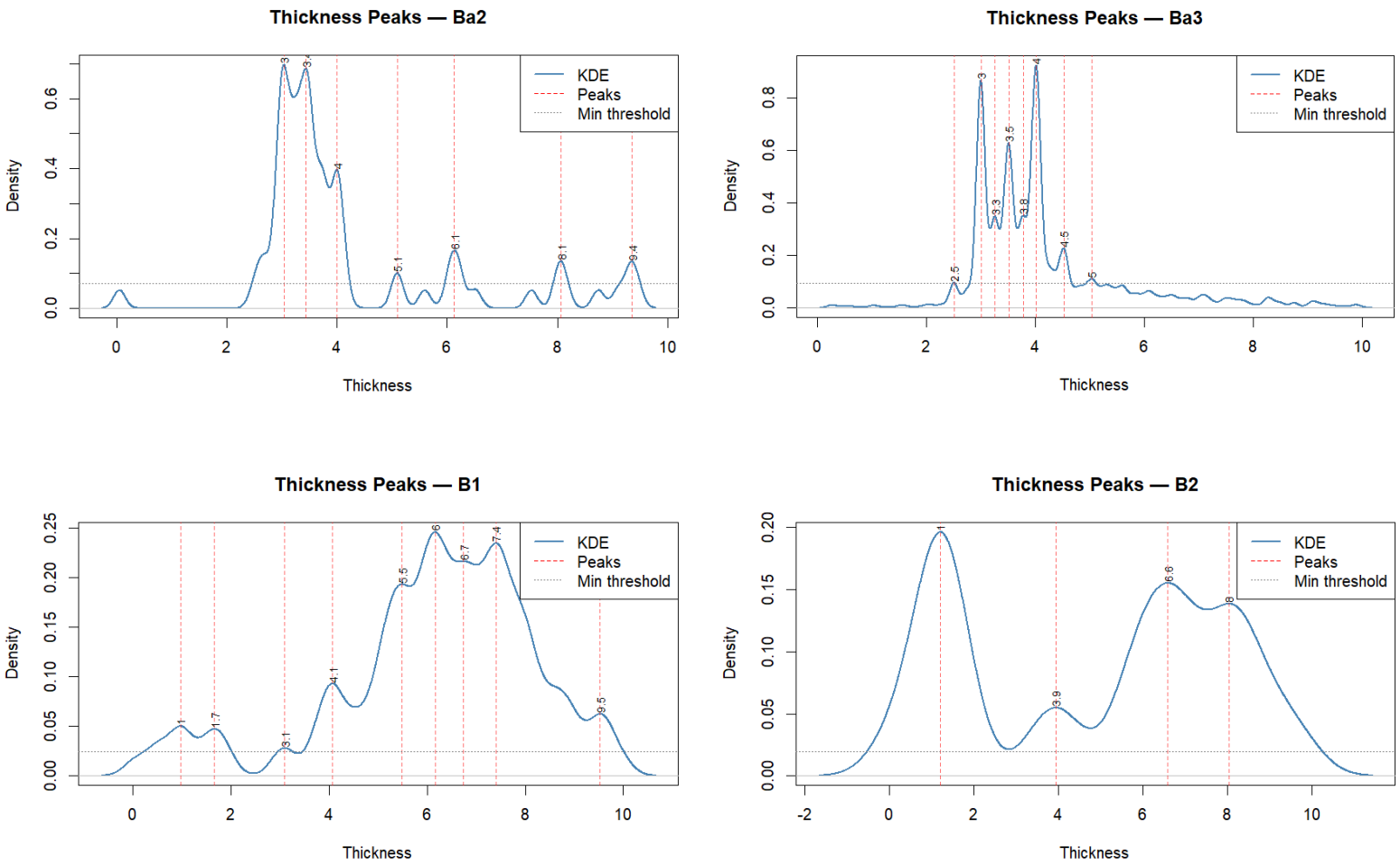
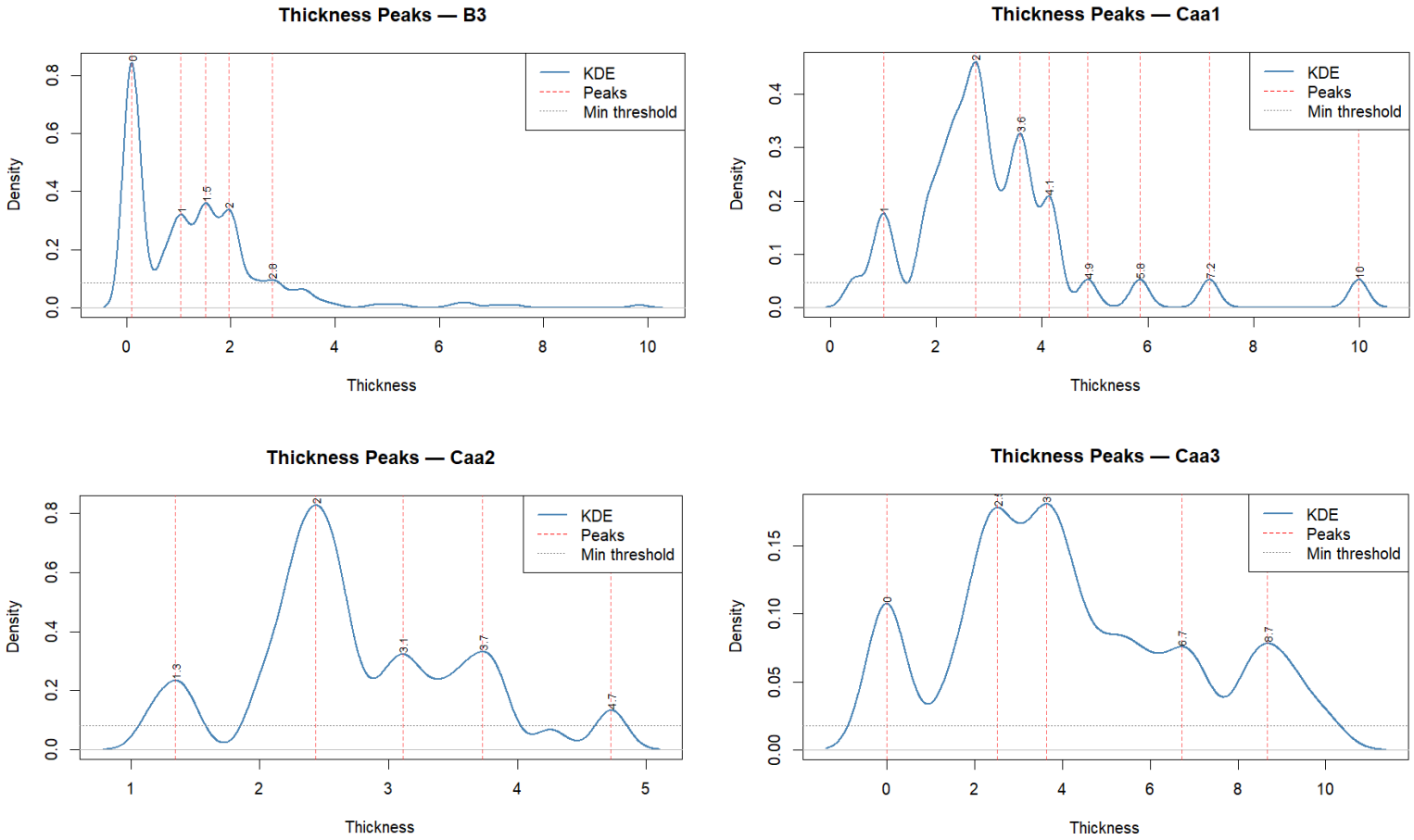


Figure H.3 - Kernel Density Estimation for Tranche Thickness (B3 through Caa3)



Appendix I "Thin" vs. "Thick" Tranche Average C-1 Factors

In the proposed factors, the Academy defines "thin" to be ≤4% thickness and "thick" to be >4% thickness. The 4% cutoff was chosen because it is a clean round number that distinguishes the two groups of Baa3 CLOs. However, within lower credit quality—Ba3 in particular—4% and 4.5% are common thicknesses. See Appendix H. The Academy thus presents 4.25% as an alternative cutoff point, as it is the midpoint of 4% and 4.5% and is within the range where no Baa3 bonds exist.

Table I.1 - Distribution of Balance by Rating and Thickness

	Distribution of Current Balance ($), by Rating and Thickness			
Rating	**Thickness ≤ 4%**	**Thickness > 4%**	**Thickness ≤ 4.25%**	**Thickness > 4.25%**
Aaa	7,019,535,647	529,970,994,807	7,953,685,647	529,036,844,807
Aa1	86,400,000	12,890,962,056	86,400,000	12,890,962,056
Aa2	303,372,000	87,668,358,271	333,372,000	87,638,358,271
Aa3	-	1,892,554,504	-	1,892,554,504
A1	283,875,000	6,180,587,500	447,875,000	6,016,587,500
A2	254,640,000	43,354,520,095	254,640,000	43,354,520,095
A3	18,750,000	1,143,245,000	18,750,000	1,143,245,000
Baa1	209,400,000	3,752,736,650	392,860,000	3,569,276,650
Baa2	148,550,000	7,966,005,000	269,650,000	7,844,905,000
Baa3	3,215,270,000	40,771,318,439	3,215,270,000	40,771,318,439
Ba1	1,276,616,000	664,139,600	1,348,236,000	592,519,600
Ba2	752,065,000	660,259,566	845,635,000	566,689,566
Ba3	14,235,703,060	15,597,030,288	18,483,360,560	11,349,372,788
B1	109,948,000	3,151,314,126	220,948,000	3,040,314,126
B2	52,739,000	369,455,200	68,739,000	353,455,200
B3	1,551,315,000	178,364,579	1,551,315,000	178,364,579
Caa1	304,189,379	265,904,272	355,036,500	215,057,151
Caa2	399,260,363	80,152,584	399,260,363	80,152,584
Caa3	236,423,988	624,413,779	250,823,988	610,013,779

Figure I.1 - Comparison of Raw C-1 Factors under 4% vs. 4.25% Tranche Thickness (Baa1 and Baa2)

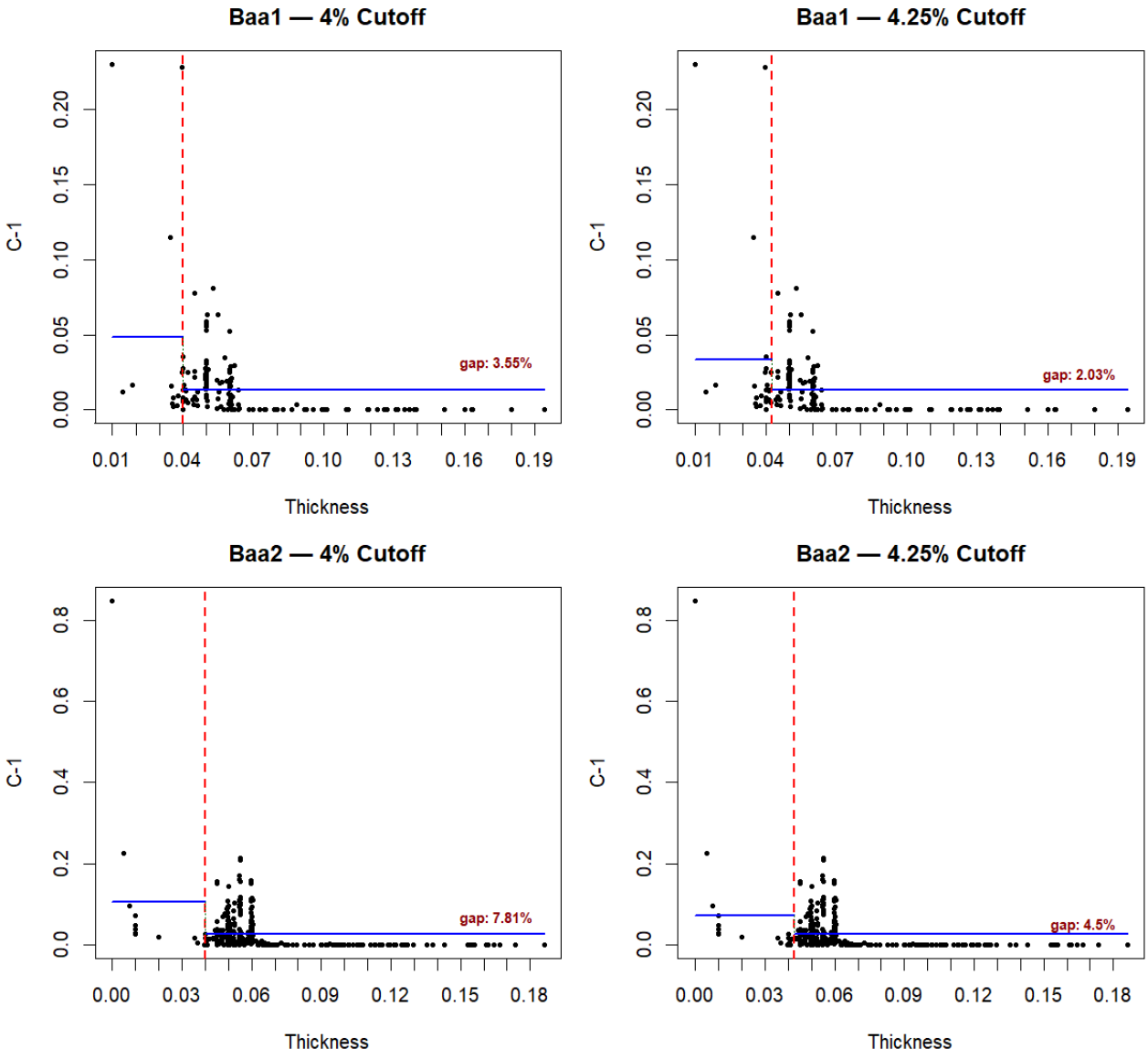


Figure I.2 - Comparison of Raw C-1 Factors under 4% vs. 4.25% Tranche Thickness (Baa3 and Ba1)

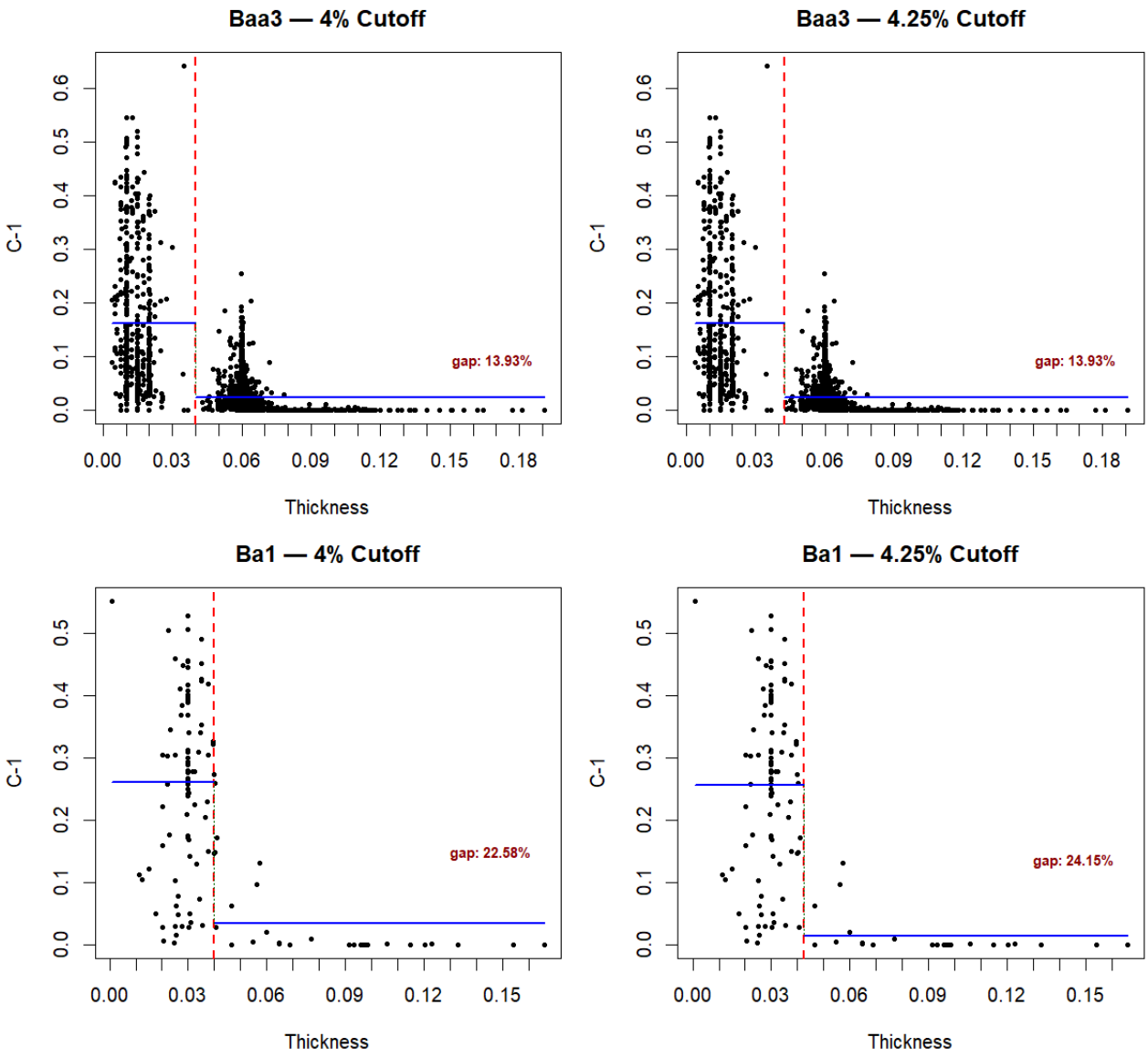


Figure I.3 - Comparison of Raw C-1 Factors under 4% vs. 4.25% Tranche Thickness (Ba2 and Ba3)

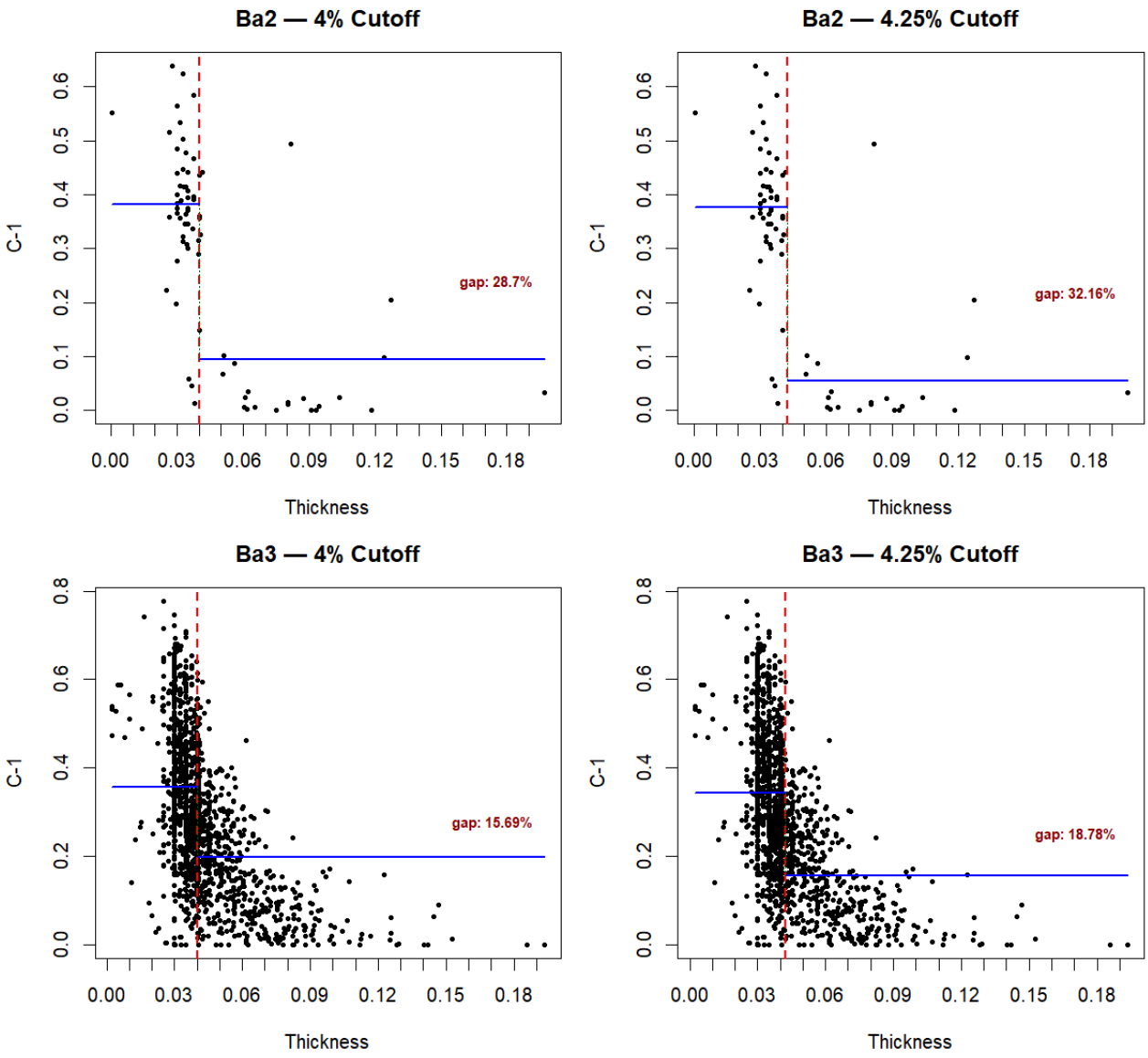


Figure I.4 - Comparison of Raw C-1 Factors under 4% vs. 4.25% Tranche Thickness (B1 and B2)

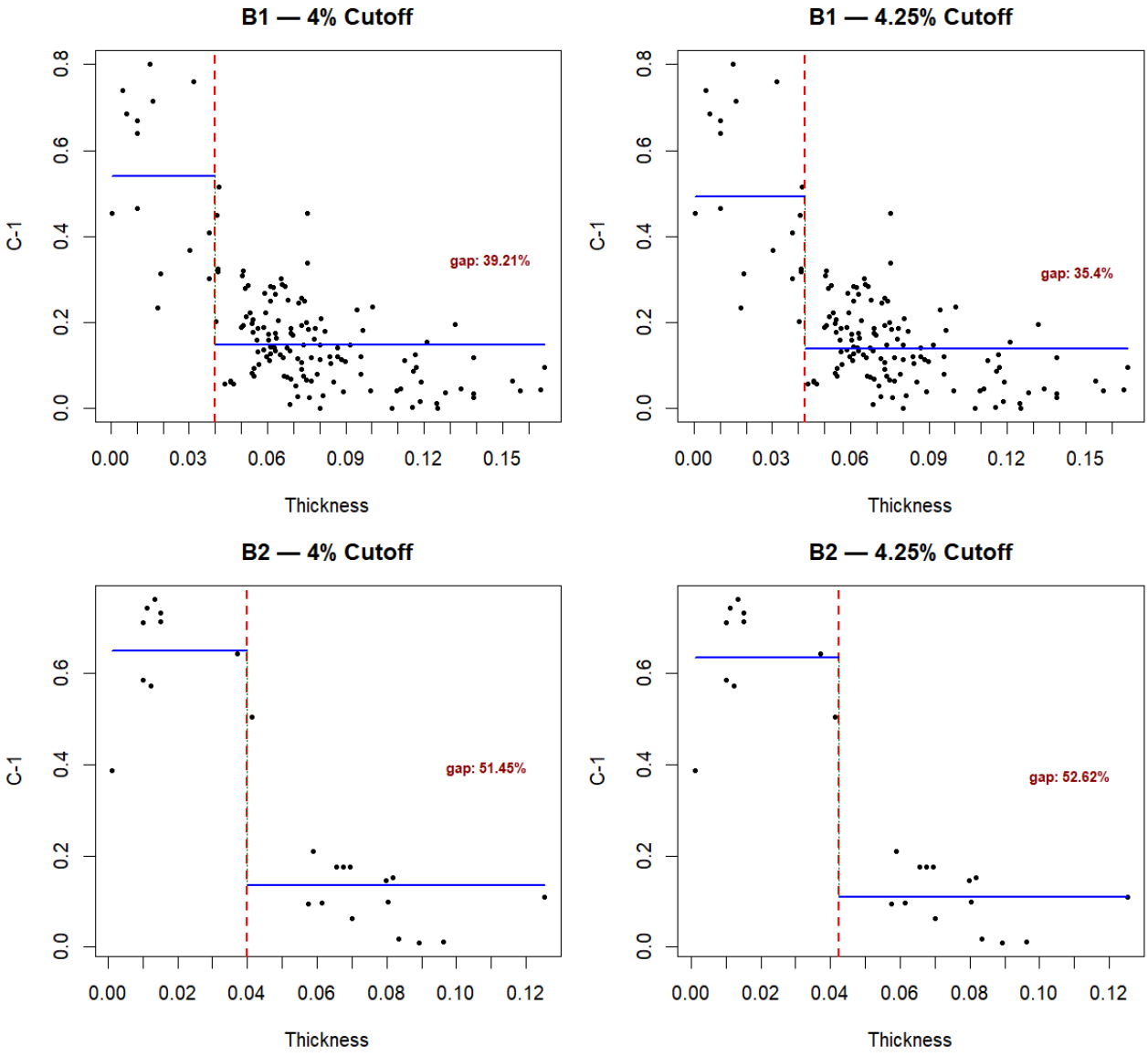


Figure I.5 - Comparison of Raw C-1 Factors under 4% vs. 4.25% Tranche Thickness (B3 and Caa1)

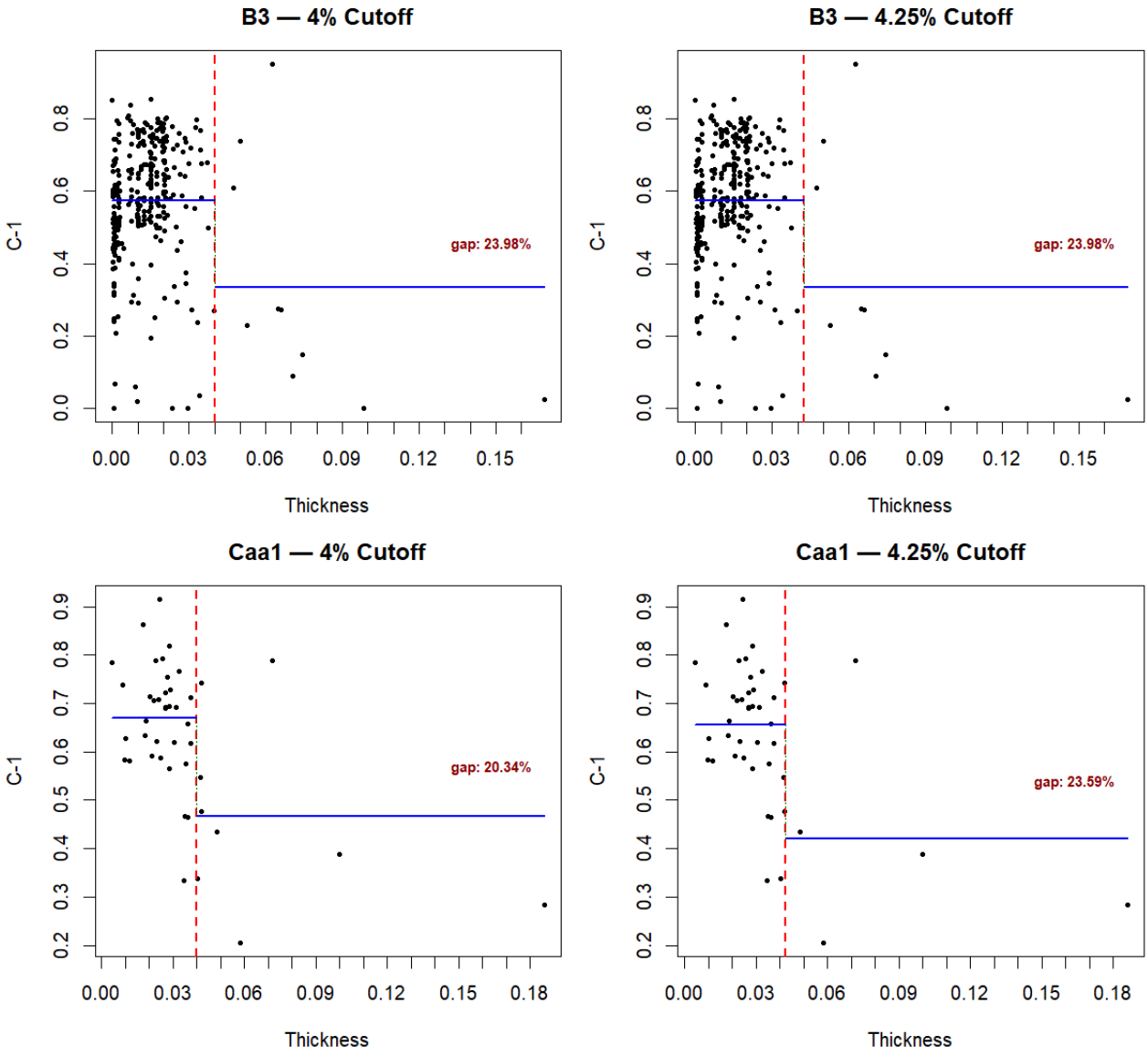
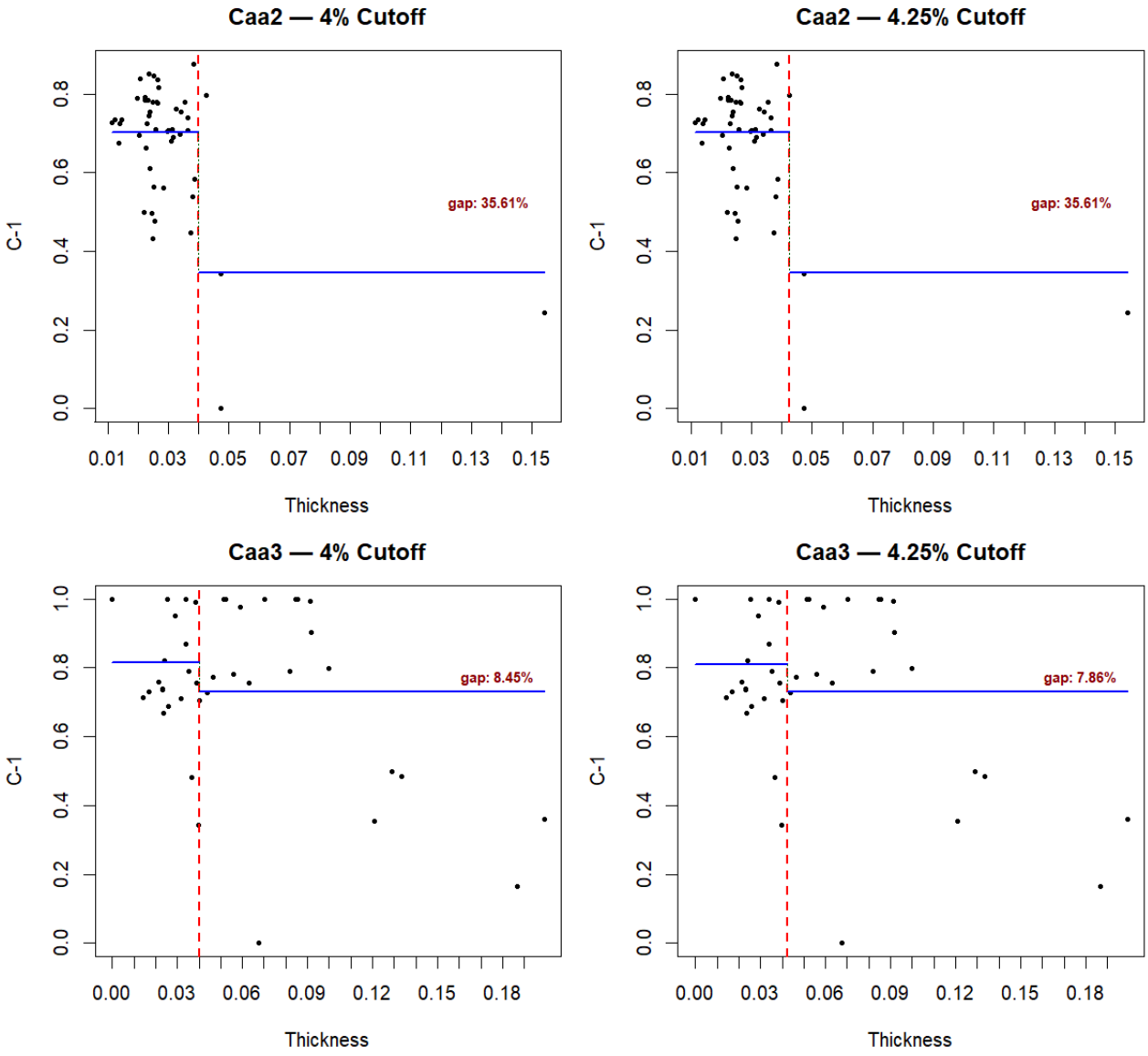


Figure I.6 - Comparison of Raw C-1 Factors under 4% vs. 4.25% Tranche Thickness (Caa2 and Caa3)



Appendix J Residual Tranche Regressions

Detachment Point, WARF, Worst Credit Rating and Interest/Principal Paid

TR_DP is the detachment point of the residual tranche.
WARF is the weighted average rating factor, as defined by Moody's Analytics.
MAX_RATING_NUM is the numeric rating (Aaa = 1, Aa1 = 2, etc.) corresponding to the CLO deal's lowest-rated debt tranche.
INT_PRIN_TO_FACE is the ratio of the sum of interest and principal already paid to the residual tranche face value.

```
Residuals:
     Min       1Q   Median       3Q      Max
-0.65564 -0.11078 -0.01858  0.09074  0.89382

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)       3.569e-01  3.484e-02  10.245  < 2e-16 ***
TR_DP            -8.333e-01  1.191e-01  -7.000 3.46e-12 ***
WARF              7.511e-05  8.925e-06   8.415  < 2e-16 ***
MAX_RATING_NUM    9.674e-03  2.058e-03   4.701 2.76e-06 ***
INT_PRIN_TO_FACE -5.466e-01  1.180e-02 -46.320  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1639 on 2060 degrees of freedom
Multiple R-squared:  0.5148,    Adjusted R-squared:  0.5139
F-statistic: 546.5 on 4 and 2060 DF,  p-value: < 2.2e-16
```

Detachment Point, WARF, Interest/Principal Paid and Ratio of CLO Balance in Low Credit Tranches

PROP_BAA1_OR_WORSE is the proportion of debt tranches rated Baa1 or worse, by balance, per CLO.

```
Residuals:
     Min       1Q   Median       3Q      Max
-0.70571 -0.10666 -0.02163  0.08987  0.88639

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)
(Intercept)         5.816e-01  2.401e-02  24.223  < 2e-16 ***
TR_DP               1.690e-02  3.554e-02   0.475 0.634534
WARF                4.785e-06  7.931e-06   0.603 0.546384
INT_PRIN_TO_FACE   -5.485e-01  1.192e-02 -46.012  < 2e-16 ***
PROP_BAA1_OR_WORSE -7.424e-02  1.660e-01  -0.447 0.654668
PROP_BA1_OR_WORSE   1.069e+00  2.580e-01   4.141 3.58e-05 ***
PROP_B1_OR_WORSE    6.605e-01  1.921e-01   3.439 0.000595 ***
PROP_CAA1_OR_WORSE -5.136e-01  1.929e-01  -2.662 0.007815 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1645 on 2141 degrees of freedom
Multiple R-squared:  0.5296,    Adjusted R-squared:  0.5281
F-statistic: 344.4 on 7 and 2141 DF,  p-value: < 2.2e-16
```

Interest/Principal Paid and Ratio of CLO Balance in Ba1 or Worse

```
Residuals:
     Min       1Q   Median       3Q      Max
-0.61871 -0.11113 -0.02463  0.08914  0.87414

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)       0.581491   0.007408   78.50   <2e-16 ***
INT_PRIN_TO_FACE -0.538276   0.011045  -48.73   <2e-16 ***
PROP_BA1_OR_WORSE 1.242745   0.087241   14.24   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.165 on 2146 degrees of freedom
Multiple R-squared:  0.5254,    Adjusted R-squared:  0.5249
F-statistic:  1188 on 2 and 2146 DF,  p-value: < 2.2e-16
```

Appendix K Stress Tests for Six Sample Deals

Sensitivities 1 and 2—Systematic Risk and Correlation

Systematic risk is modeled with pairwise correlation between loans. The baseline correlation is 10%. Li and Chen (2018) reference 2%, 35%, and 51% in 1-year, 5-year, and 10-year correlations for B-rated issuers. Qi et al. (2019) reference 2%, 10%, and 9% in 1-year, 5-year, and 10-year correlations for B-rated issuers.

Table K.1 - Raw C-1 Factors on Sample Deals for Sensitivities 1 and 2

Rating \ Raw C-1 Factor	Baseline	Sensitivity 1 5% Corr	Sensitivity 2 20% Corr
Aaa	0.00%	0.00%	0.00%
Aa2	0.00%	0.00%	0.05%
A2	0.04%	0.01%	1.24%
Baa2	0.89%	0.04%	8.17%
Baa3	2.34%	0.80%	12.58%
Ba3	30.72%	20.18%	52.93%

Sensitivity 3—Copula

The baseline assumption is a Gaussian copula. The Clayton copula may capture the asymmetric distribution of default correlations and produces fatter tails.

Table K.2 - Raw C-1 Factors on Sample Deals for Sensitivity 3

Rating \ Raw C-1 Factor	Baseline	Sensitivity 3 Clayton Copula
Aaa	0.00%	0.00%
Aa2	0.00%	0.00%
A2	0.04%	0.08%
Baa2	0.89%	2.21%
Baa3	2.34%	7.57%
Ba3	30.72%	34.04%

Sensitivity 4—Correlation in Severities

The baseline assumption is no correlation between recovery rates. This sensitivity tests correlated recovery rates using a Gaussian copula with 10% correlation. If recoveries are correlated with the rate of default—for example, high default environments producing lower recoveries—then recoveries will be correlated with one another.

Table K.3 - Average Raw C-1 Factors on Sample Deals for Sensitivity 4

Rating \ Raw C-1 Factor	Baseline	Sensitivity 4 Correlated Severities
Aaa	0.00%	0.00%
Aa2	0.00%	0.00%
A2	0.04%	0.29%
Baa2	0.89%	3.73%
Baa3	2.34%	8.51%
Ba3	30.72%	42.38%

Sensitivity 5—Recovery Average

The baseline assumption uses S&P average loss given default: 27% for senior secured loans and 60% for senior unsecured loans. A higher LGD is tested: 36% for senior secured and 54% for senior unsecured. Despite the lower LGD on senior unsecured, the overall LGD is higher in the sensitivity because the vast majority of CLO collateral is senior secured. In both cases, simple averages are not the direct input. The model uses decile data published by S&P so that the tail of the recovery distribution could be captured, and the averages for the sensitivity are fitted to the shape of S&P deciles by least-squares optimization.

Table K.4 - Average Raw C-1 Factors on Sample Deals for Sensitivity 5

Rating \ Raw C-1 Factor	Baseline	Sensitivity 5 Lower Recovery
Aaa	0.00%	0.00%
Aa2	0.00%	0.00%
A2	0.04%	1.77%
Baa2	0.89%	21.73%
Baa3	2.34%	19.62%
Ba3	30.72%	59.09%

Sensitivities 6 and 7—Collateral Repurchase Price and Prepayment

The baseline scenario models no prepayments and no repurchase discounts. These sensitivities model historically low prepayment speeds and purchase prices, consistent with stressed credit environments. Sensitivity 6 corresponds to the average of every observation less than or equal to the 10th percentile of the historical data of each of the prepayment speeds and purchase prices, corresponding to an 11.8% prepayment rate and a purchase price of 82.5. Sensitivity 7 applies prepayment and repurchase price equal to the VaR0.5 of historical data, corresponding to an 8.7% prepayment rate and a purchase price of 72.0.

Table K.5 - Average Raw C-1 Factors on Sample Deals for Sensitivities 6 and 7

Rating \ Raw C-1 Factor	Baseline	Sensitivity 6 Prepay & Discount A	Sensitivity 7 Prepay & Discount B
Aaa	0.00%	0.00%	0.00%
Aa2	0.00%	0.00%	0.00%
A2	0.04%	0.07%	0.07%
Baa2	0.89%	0.00%	0.00%
Baa3	2.34%	0.55%	0.37%
Ba3	30.72%	10.15%	6.67%

Table K.6 - Raw C-1 Factors by Sample Deal for Sensitivity 6

Rating \ Raw C-1 Factor	Average	Carlyle 2021-1	Strata II	Ares 52	Magnetite 27	OHA 3	Anchorage 17
Aaa	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Aa2	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
A2	0.07%	0.00%	0.00%	0.00%	0.00%	0.41%	0.00%
Baa2	0.00%	0.00%	n/a	n/a	n/a	n/a	n/a
Baa3	0.55%	0.00%	1.89%	0.83%	0.00%	0.60%	0.00%
Ba3	10.15%	0.00%	15.43%	31.11%	5.45%	1.22%	7.66%

Table K.7 - Raw C-1 Factors by Sample Deal for Sensitivity 7

Rating \ Raw C-1 Factor	Average	Carlyle 2021-1	Strata II	Ares 52	Magnetite 27	OHA 3	Anchorage 17
Aaa	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Aa2	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
A2	0.07%	0.00%	0.00%	0.00%	0.00%	0.41%	0.00%
Baa2	0.00%	0.00%	n/a	n/a	n/a	n/a	n/a
Baa3	0.37%	0.00%	0.81%	0.79%	0.00%	0.60%	0.00%
Ba3	6.67%	0.00%	10.00%	28.68%	0.01%	1.22%	0.13%

Sensitivities 8 and 9—Recovery, Prepayment, and Repurchase Price Combined

These sensitivities combine the lower recovery average assumption with the prepayment and repurchase price discounts tested individually above. Sensitivity 8 combines Sensitivities 5 and 6. Sensitivity 9 combines Sensitivities 5 and 7.

Table K.8 - Average Raw C-1 Factors on Sample Deals for Sensitivities 8 and 9

Rating \ Raw C-1 Factor	Baseline	Sensitivities 5 & 6	Sensitivities 5 & 7
Aaa	0.00%	0.00%	0.00%
Aa2	0.00%	0.00%	0.00%
A2	0.04%	0.20%	0.11%
Baa2	0.89%	0.00%	0.00%
Baa3	2.34%	5.51%	3.43%
Ba3	30.72%	31.12%	23.27%

Appendix L Bayesian Estimate of Frequency

Let *X* denote the observed number of default events and *Y* denote the total number of exposure trials, so that the observed (frequentist) default rate is *X* / *Y*. The objective is to estimate the true underlying default probability *p*, incorporating prior belief alongside the observed data.

Under the assumption that defaults occur independently and with constant probability *p*, the number of defaults *X* follows a Binomial distribution:

$$P(X|p,Y) = C(Y,X) \times p^X \times (1-p)^{Y-X}.$$

A flat, non-informative prior is assigned to *p*, reflecting equal prior probability across all values of $p \in [0,1]$. This Uniform distribution is equivalent to $p \sim Beta(\alpha, \beta)$ with $\alpha = 1$, $\beta = 1$.

Because the Beta distribution is the conjugate prior for the Binomial likelihood, the posterior distribution of *p* given the observed data is also a Beta distribution and is obtained analytically via Bayes' theorem:

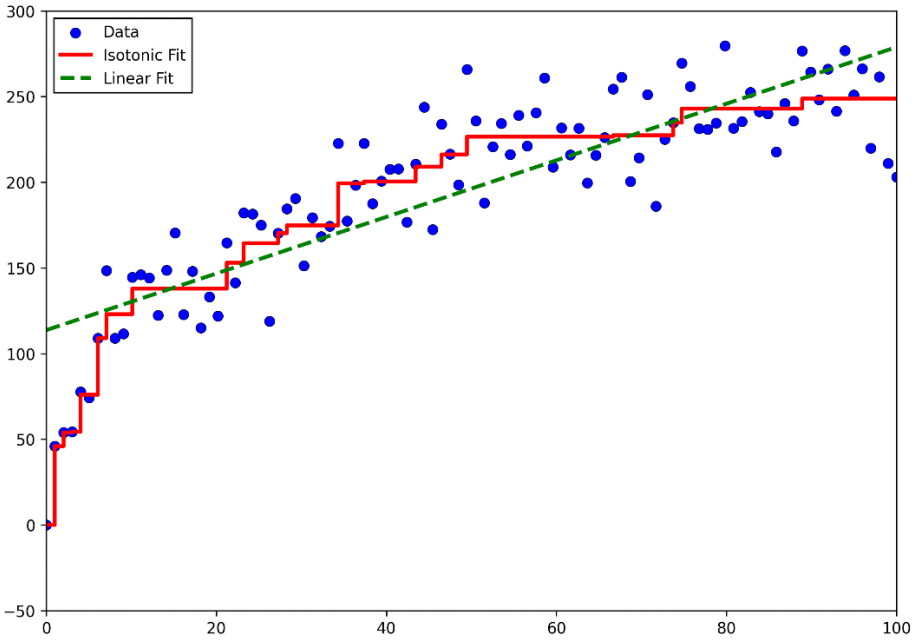
$$P(p|X,Y) \propto P(X|p,Y) \times P(p).$$

Then, $p|X,Y \sim Beta(\alpha + X, \beta + Y - X) = Beta(1 + X, 1 + Y - X)$. The expected value of a variable with beta distribution $Beta(a,b)$ is $\frac{a}{a+b}$. Therefore,

$$E[p|X,Y] = \frac{1+X}{(1+X)+(1+Y-X)} = \frac{1+X}{2+Y}.$$

Appendix M Isotonic Regression

Figure M.1 - Illustrative Isotonic vs. Linear Regression Fit



For $x_1 \leq x_2 \leq \cdots \leq x_n$, the isotonic regression solves:

$$\min_{\hat{y}_1, \ldots, \hat{y}_n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \;\; s.t. \;\; \hat{y}_1 \leq \hat{y}_2 \leq \cdots \leq \hat{y}_n$$

The isotonic regression forces monotonicity, i.e., constrains data to be non-decreasing. The result is a stepwise fit where the steps correspond to weighted averages of the local points.

The Pool-Adjacent-Violators (PAV) algorithm starts with $y_i = \hat{y}_i$ and identifies points where $\hat{y}_i > \hat{y}_{i+1}$. When violations occur, the two adjacent steps are averaged together (weighted by number of points) until monotonicity is achieved.

Appendix N CLO Ownership in 2024YE Statutory Filings

The Academy synthesizes 2024 year-end statutory filings into the table below, identifying the number of unique CLOs and the credit distribution thereof for each company (company names are scrubbed). Statutory filings are processed by S&P Global and CLOs are identified by Neuberger in the provided data. All companies are evaluated at the group level. Analysis of CLOs relative to total *Schedule D1* assets is limited to unaffiliated general account assets.

Table N.1 - Unique CLO Deals, CLO Book Value and CLO Credit Distribution by Life Insurer, 2024YE

# Unique CLO Deals	CLO Debt BV ($mn)	D1 BV ($mn)	Total Cash & Invested Assets ($mn)	CLO : D1 (%)	CLO : Total Assets (%)	Distribution of NAIC Credit Designations (%)								
						1A	1B-1C-1D	1E-1F-1G	2	3	4	5	6	None
811	21,236	205,624	333,781	10	6	59	24	7	5	4	0	0	-	-
753	5,107	43,589	57,759	12	9	18	13	33	25	10	0	-	0	0
737	22,175	136,395	226,890	16	10	11	25	36	28	0	-	-	0	-
605	3,870	33,060	44,631	12	9	26	34	35	5	0	0	0	-	-
574	9,599	169,969	235,439	6	4	30	33	28	9	0	0	-	0	-
501	6,370	89,179	140,199	7	5	74	25	0	-	0	0	-	-	-
466	6,821	100,220	163,078	7	4	39	31	24	6	1	0	0	-	-
457	2,372	15,699	28,168	15	8	3	3	17	64	4	8	0	1	-
443	6,922	24,826	49,839	28	14	6	5	17	59	12	1	0	0	-
424	3,539	68,358	110,475	5	3	44	39	9	8	-	-	-	-	-
387	1,970	22,386	31,989	9	6	8	6	13	55	17	0	0	-	-
387	2,197	51,033	77,488	4	3	40	39	11	9	1	0	-	-	-
374	4,266	87,997	118,480	5	4	8	58	27	6	1	1	-	-	-
359	5,189	59,143	89,594	9	6	44	18	21	15	3	-	-	-	-
330	5,367	151,802	264,775	4	2	45	31	15	7	1	0	-	-	-
316	2,624	53,875	90,526	5	3	11	10	36	34	7	1	0	-	-
312	8,704	36,755	50,203	24	17	44	21	20	14	1	-	-	-	-
307	2,260	61,754	81,273	4	3	8	13	77	1	0	-	-	-	-
285	737	4,939	6,403	15	12	40	35	22	3	-	-	-	-	0
285	1,930	28,816	38,652	7	5	5	24	65	6	0	1	0	0	-
265	9,485	255,985	349,536	4	3	74	19	6	1	0	0	-	-	0
251	1,405	25,119	31,876	6	4	9	16	11	5	53	7	-	0	-
247	1,072	7,855	9,572	14	11	4	9	12	63	10	2	-	1	-
241	751	6,377	7,604	12	10	4	5	23	56	13	-	-	-	-
239	950	18,607	32,526	5	3	40	36	1	8	15	-	-	-	-
238	8,526	201,782	323,918	4	3	78	22	0	0	-	-	-	-	-
233	1,421	22,803	31,939	6	4	14	38	27	21	0	0	0	0	0
222	2,185	15,210	23,436	14	9	32	19	44	6	0	-	-	-	-
206	2,652	29,512	42,946	9	6	8	21	16	37	13	2	1	-	0
204	1,378	19,497	24,735	7	6	15	11	29	40	4	1	-	-	-
191	2,087	27,924	35,779	7	6	36	37	12	14	1	-	-	-	-
180	1,433	14,293	21,584	10	7	13	4	46	37	-	-	-	-	-
177	3,528	101,514	182,523	3	2	54	46	0	0	0	-	-	-	-
175	1,060	24,678	30,141	4	4	28	48	19	3	1	-	0	-	-

# Unique CLO Deals	CLO Debt BV ($mn)	D1 BV ($mn)	Total Cash & Invested Assets ($mn)	CLO : D1 (%)	CLO : Total Assets (%)	Distribution of NAIC Credit Designations (%)								
						1A	1B-1C-1D	1E-1F-1G	2	3	4	5	6	None
171	1,147	9,564	15,809	12	7	19	23	25	21	9	3	0	0	-
167	1,173	17,741	22,878	7	5	10	21	30	40	-	-	-	-	-
163	1,201	11,028	15,206	11	8	63	22	4	11	1	-	-	-	-
162	3,535	49,601	70,599	7	5	38	13	20	30	0	-	-	-	-
156	5,045	90,878	115,129	6	4	52	19	21	4	3	2	-	-	-
156	1,263	31,202	43,446	4	3	19	23	45	12	1	-	-	-	-
153	364	3,838	4,383	9	8	11	12	7	4	56	8	2	-	-
144	656	27,567	31,817	2	2	47	38	8	6	1	0	-	-	-
143	1,562	20,887	28,283	7	6	25	50	19	1	5	0	-	-	-
142	163	2,822	3,225	6	5	69	26	6	-	-	-	-	-	-
141	1,728	16,397	22,368	11	8	20	15	37	25	3	1	-	-	-
141	7,446	85,579	116,968	9	6	73	22	4	1	0	-	-	-	-
140	138	1,258	1,763	11	8	40	14	3	41	1	1	-	-	-
139	2,816	47,947	68,052	6	4	47	40	12	1	-	-	-	-	-
135	355	2,344	3,822	15	9	0	3	25	70	2	-	-	-	-
122	1,061	39,141	47,574	3	2	48	17	15	5	3	1	-	11	-
121	2,290	61,501	88,651	4	3	55	27	16	3	-	0	-	-	-
120	487	4,280	5,381	11	9	-	10	2	67	21	-	-	-	-
114	1,226	13,132	18,732	9	7	66	21	9	2	1	0	-	-	-
110	282	4,698	6,294	6	4	5	63	32	-	-	-	-	-	-
106	266	1,316	1,767	20	15	-	2	27	62	9	-	-	-	-
105	1,484	214,163	310,386	1	0	43	48	1	2	1	0	1	4	-
104	980	12,964	16,409	8	6	53	47	-	-	-	0	-	0	-
103	302	3,546	6,135	9	5	33	16	19	32	0	0	-	-	-
100	412	3,755	4,655	11	9	92	5	3	-	-	-	-	-	-
99	412	4,184	4,605	10	9	44	16	19	19	3	-	-	-	-
98	306	891	1,196	34	26	4	3	10	74	8	-	-	-	-
98	1,511	33,934	46,016	4	3	32	44	20	3	1	-	-	-	-
96	203	2,675	3,417	8	6	30	27	25	13	1	1	3	-	-
95	2,649	39,590	61,907	7	4	56	32	9	3	-	-	-	-	-
93	64	1,740	1,883	4	3	88	12	-	-	-	-	-	-	-
92	202	514	694	39	29	4	1	10	75	10	-	-	-	0
88	169	2,391	2,757	7	6	-	26	57	17	-	-	-	-	-
88	42	2,489	3,038	2	1	35	29	36	-	-	-	-	-	-
82	107	10,401	15,824	1	1	9	30	27	34	-	-	-	-	-

# Unique CLO Deals	CLO Debt BV ($mn)	D1 BV ($mn)	Total Cash & Invested Assets ($mn)	CLO : D1 (%)	CLO : Total Assets (%)	Distribution of NAIC Credit Designations (%)								
						1A	1B-1C-1D	1E-1F-1G	2	3	4	5	6	None
77	320	7,259	8,930	4	4	32	23	28	17	-	-	-	-	-
76	385	3,842	5,960	10	6	47	45	4	4	-	-	-	-	-
76	215	4,085	4,806	5	4	10	49	22	18	1	-	-	-	-
75	118	519	874	23	13	2	7	9	82	-	-	-	-	-
72	97	1,173	1,431	8	7	1	29	52	19	-	-	-	-	-
69	900	34,726	54,106	3	2	47	26	16	11	1	0	-	-	-
68	152	9,910	15,657	2	1	73	18	6	3	-	-	-	-	-
67	911	53,004	79,856	2	1	37	63	-	-	-	-	-	0	-
64	60	2,314	3,732	3	2	25	13	30	18	14	-	-	-	-
63	37	1,431	1,658	3	2	38	29	33	-	-	-	-	-	-
59	88	872	1,225	10	7	17	67	10	6	-	-	-	-	-
59	497	6,130	7,498	8	7	16	39	28	11	6	-	-	-	-
57	75	479	492	16	15	14	57	29	-	-	-	-	-	-
56	199	3,517	4,952	6	4	47	40	5	8	-	-	-	-	-
54	168	15,178	22,996	1	1	-	59	40	-	-	-	-	-	0
53	116	7,733	10,780	1	1	17	19	11	52	-	-	-	-	1
50	162	877	1,059	18	15	22	17	3	58	-	-	-	-	-
48	77	2,836	3,205	3	2	1	4	31	64	-	-	-	-	-
47	227	13,478	17,197	2	1	41	46	13	-	-	-	-	-	-
46	646	25,349	30,881	3	2	62	38	-	-	-	-	-	-	-
46	477	54,120	79,176	1	1	46	18	20	3	9	3	-	1	-
45	108	879	1,099	12	10	19	78	3	-	-	-	-	-	-
44	337	8,598	11,955	4	3	61	31	8	-	-	-	-	-	-
43	362	3,453	10,205	10	4	-	11	29	61	-	-	-	-	-
42	51	955	1,201	5	4	38	36	16	6	-	-	2	2	-
42	161	3,076	3,776	5	4	8	3	50	38	2	-	-	-	-
42	258	42,688	56,816	1	0	34	47	16	3	-	-	-	-	-
40	146	5,219	6,440	3	2	-	36	19	25	-	14	2	5	-
38	137	2,567	3,435	5	4	58	40	1	1	1	0	-	-	-
37	164	874	1,026	19	16	45	34	18	2	-	-	-	-	-
37	362	8,226	10,315	4	4	80	16	-	3	-	-	0	0	-
36	479	9,720	14,917	5	3	16	47	31	3	2	-	-	-	-
36	21	735	872	3	2	40	20	20	19	-	-	-	-	-
35	128	1,472	1,808	9	7	1	0	3	10	81	-	-	-	4
33	258	3,628	3,873	7	7	12	79	3	4	3	-	-	-	-

# Unique CLO Deals	CLO Debt BV ($mn)	D1 BV ($mn)	Total Cash & Invested Assets ($mn)	CLO : D1 (%)	CLO : Total Assets (%)	Distribution of NAIC Credit Designations (%)								
						1A	1B-1C-1D	1E-1F-1G	2	3	4	5	6	None
32	35	987	1,158	4	3	20	55	20	5	-	-	-	-	-
31	49	297	629	16	8	3	2	1	4	85	5	-	-	-
30	41	1,157	1,743	4	2	33	30	36	-	-	-	-	-	-
29	62	2,003	2,415	3	3	45	34	3	18	-	-	-	-	-
29	46	2,256	3,031	2	2	26	41	34	-	-	-	-	-	-
28	22	119	219	18	10	2	7	28	63	-	-	-	-	-
28	35	1,318	1,627	3	2	36	64	-	-	-	-	-	-	-
27	91	2,381	2,798	4	3	20	53	26	-	-	-	-	-	-
27	43	3,287	4,088	1	1	23	76	1	-	-	-	-	-	-
26	114	13,358	18,067	1	1	3	91	6	-	-	-	-	-	-
25	90	2,778	3,629	3	2	12	30	28	31	-	-	-	-	-
25	7	1,897	2,064	0	0	45	26	24	5	-	-	-	-	-
20	47	258	302	18	15	-	-	61	39	-	-	-	-	-
20	129	2,452	2,783	5	5	15	35	35	15	-	-	-	-	-
20	52	1,922	2,737	3	2	7	50	43	-	-	-	-	-	-
20	12	1,149	1,376	1	1	80	20	-	-	-	-	-	-	-
19	46	1,774	2,309	3	2	41	59	-	-	-	-	-	-	-
19	5	192	239	2	2	35	38	27	-	-	-	-	-	-
19	143	6,487	10,184	2	1	27	36	35	1	-	-	-	-	1
18	9	112	191	8	5	8	13	78	-	-	-	-	-	-
18	8	960	1,007	1	1	29	51	21	-	-	-	-	-	-
17	28	235	367	12	8	-	8	5	83	3	-	-	-	-
17	150	3,556	4,560	4	3	1	15	35	30	10	9	-	-	-
17	97	3,412	4,066	3	2	59	41	-	-	-	-	-	-	-
15	12	492	611	2	2	59	41	-	-	-	-	-	-	-
15	21	2,552	2,925	1	1	100	-	-	-	-	-	-	-	-
14	16	505	572	3	3	89	6	4	-	-	-	-	-	-
13	4	102	215	4	2	46	54	-	-	-	-	-	-	-
13	198	33,208	38,597	1	1	97	3	-	-	-	-	-	-	-
12	5	80	147	6	3	22	22	7	49	-	-	-	-	-
12	33	1,072	1,372	3	2	26	53	6	16	-	-	-	-	-
11	34	290	511	12	7	-	-	9	74	17	-	-	-	-
11	26	1,590	1,818	2	1	66	26	8	-	-	-	-	-	-
10	9	474	561	2	2	2	4	-	94	-	-	-	-	-
10	4	276	292	2	1	100	-	-	-	-	-	-	-	-

# Unique CLO Deals	CLO Debt BV ($mn)	D1 BV ($mn)	Total Cash & Invested Assets ($mn)	CLO : D1 (%)	CLO : Total Assets (%)	Distribution of NAIC Credit Designations (%)								
						1A	1B-1C-1D	1E-1F-1G	2	3	4	5	6	None
9	10	80	119	12	8	-	-	-	100	-	-	-	-	-
9	50	609	662	8	8	84	16	-	-	-	-	-	-	-
9	38	1,517	1,728	2	2	17	-	63	20	-	-	-	-	-
9	28	1,159	1,217	2	2	19	81	-	-	-	-	-	-	-
8	2	68	78	2	2	100	-	-	-	-	-	-	-	-
7	7	233	391	3	2	100	-	-	-	-	-	-	-	-
7	3	112	140	2	2	60	20	20	-	-	-	-	-	-
7	18	1,028	1,060	2	2	-	100	-	-	-	-	-	-	-
7	5	365	496	1	1	71	29	-	-	-	-	-	-	-
7	6	425	458	1	1	10	90	-	-	-	-	-	-	-
7	8	828	940	1	1	-	100	-	-	-	-	-	-	-
7	2	467	566	0	0	21	32	47	-	-	-	-	-	-
6	3	163	252	2	1	34	66	-	-	-	-	-	-	-
6	2	122	124	1	1	100	-	-	-	-	-	-	-	-
6	2	185	223	1	1	46	27	27	-	-	-	-	-	-
6	4	479	582	1	1	60	17	23	-	-	-	-	-	-
6	16	7,725	9,869	0	0	100	-	-	-	-	-	-	-	-
5	5	25	55	19	9	100	-	-	-	-	-	-	-	-
5	5	176	202	3	3	36	64	-	-	-	-	-	-	-
5	5	313	367	2	1	100	-	-	-	-	-	-	-	-
5	3	218	264	2	1	82	18	-	-	-	-	-	-	-
5	2	178	210	1	1	58	21	21	-	-	-	-	-	-
4	4	196	219	2	2	100	-	-	-	-	-	-	-	-
4	2	142	149	1	1	26	24	25	25	-	-	-	-	-
4	3	307	599	1	0	-	16	84	-	-	-	-	-	-
4	2	216	271	1	1	69	-	31	-	-	-	-	-	-
4	1	148	171	1	1	52	48	-	-	-	-	-	-	-
4	2	1,093	1,249	0	0	100	-	-	-	-	-	-	-	-
4	93	62,590	112,713	0	0	100	-	-	-	-	-	-	-	-
3	4	22	22	19	18	100	-	-	-	-	-	-	-	-
3	2	102	110	1	1	50	50	-	-	-	-	-	-	-
3	1	141	179	1	0	38	-	62	-	-	-	-	-	-
3	1	9,987	20,760	0	0	-	-	-	-	-	-	-	-	100
2	0	20	29	1	1	50	-	50	-	-	-	-	-	-
1	2	33	38	6	5	-	100	-	-	-	-	-	-	-

# Unique CLO Deals	CLO Debt BV ($mn)	D1 BV ($mn)	Total Cash & Invested Assets ($mn)	CLO : D1 (%)	CLO : Total Assets (%)	Distribution of NAIC Credit Designations (%)								
						1A	1B-1C-1D	1E-1F-1G	2	3	4	5	6	None
1	2	55	58	3	3	-	100	-	-	-	-	-	-	-
1	2	116	184	1	1	-	100	-	-	-	-	-	-	-
1	24	2,022	2,555	1	1	56	15	-	11	-	-	-	-	18
1	1	147	180	1	1	-	-	51	49	-	-	-	-	-
1	0	3	30	1	0	-	-	-	-	-	-	-	100	-
1	0	8	12	1	0	100	-	-	-	-	-	-	-	-
1	8	1,539	2,364	0	0	-	-	92	8	-	-	-	-	-
1	1	114	123	0	0	100	-	-	-	-	-	-	-	-
1	2	414	448	0	0	-	-	100	-	-	-	-	-	-
1	1	209	344	0	0	100	-	-	-	-	-	-	-	-
1	1	177	195	0	0	-	-	100	-	-	-	-	-	-
1	0	217	253	0	0	-	100	-	-	-	-	-	-	-
1	0	35	94	0	0	100	-	-	-	-	-	-	-	-
1	0	91	93	0	0	100	-	-	-	-	-	-	-	-
1	0	449	503	0	0	-	100	-	-	-	-	-	-	-
1	1	887	1,171	0	0	-	100	-	-	-	-	-	-	-
1	1	1,542	1,712	0	0	-	-	-	-	-	-	100	-	-
1	1	1,108	1,394	0	0	-	100	-	-	-	-	-	-	-
1	0	618	723	0	0	100	-	-	-	-	-	-	-	-

Appendix O CDOnet Assumptions

Field Name	Description	Commentary	Decision
Optional Redemption	Optional redemption assumptions	When a CLO has a low balance and expenses from the admin, trustee, etc., it may make sense to close the CLO.	Not modeled
Interest on Cash	Interest rate earned on cash	Money market rate/risk free rate; SOFR - 50/75 because SOFR tends to be higher than money market	SOFR minus 75 bps
Intra-Period Reinvestment	Reinvestment of proceeds within the period. Reinvested assets start accruing interest immediately (if reinvestment rate is set)	Reinvested assets start accruing interest immediately (if a reinvestment rate is set). The model adjusts both principal and accrued interest based on intra-period reinvestments, tracks interest accrual within the period and includes it in the interest income available for the next payment date.	All par reinvested before payment date
Already Defaulted Severity (%)	% loss on assets already defaulted	Assigns different severity to current defaulted population and future defaults	Match rates on all other collateral
Recovery Lag	Time lag of the recovery from defaulted loan	Recovery occurs immediately	Recovery occurs immediately
Monthly Rate during Initial Recov Lag	Monthly recovery rate	The rate at which recovery cash flows are received each month during the lag period immediately after a loan defaults. Most CLO models assume this is 0%, meaning recoveries start only after a full lag. Adjusting it upward assumes partial early recoveries, which shortens the cash flow impact of a default.	0%
Prepay	Conditional prepayment rate	Most CLOs experience 5–15% annual prepayment rates in normal environments; NAIC assumes 0% rate	0%
Rate Modification	Interest rate modification on the collateral loan	Set at individual loan level: 50 bps means a loan currently earning SOFR + 400 will be modeled at SOFR + 350; this will impact excess spread and IC test	Not modeled
Balance Forgiveness Rate	Percentage of a loan's outstanding principal balance that is written off (forgiven) in a restructuring or modification scenario.	If set to 0%, no loans are in forgiveness	Not modeled
Forbearance Rate	Percentage of the scheduled interest (and/or principal) payments that are not received during a forbearance period, due to a temporary agreement between lender and borrower (forbearance rate)	If set to 0%, no loans are in forbearance	Not modeled
Forbearance Paydown	Rate at which forbearance loans are expected to pay down.	A value of 0% means no special paydown is assumed for those loans	Not modeled
Forbearance Recovery	Recovery rate of forbearance balance	100% means no loss for the forbearance loans	Not modeled
Default Scenario Multiplier	Probability of default scaling factor	100% means 1x of base case PD, i.e., no special adjustment	All factors set to 1.0
Severity Scenario Multiplier	Loss-given-default scaling factor	100% means 1x of base case scenario, i.e., no extra stress	All factors set to 1.0

Field Name	Description	Commentary	Decision
Forbearance Scenario Multiplier	Scaling factor applied to the percentage of forbearance balance	Not applicable if 0% forbearance rate	All factors set to 1.0
Balance Forgiveness Scenario Multiplier	Scaling factor applied to the percentage of forgiveness balance	Not applicable if 0% forgiveness rate	All factors set to 1.0
Forbearance Recovery Scenario Multiplier	Scaling factor applied to the percentage of the recovery rate of forbearance balance	Not applicable if 0% forbearance rate	All factors set to 1.0
Prepay Scenario Multiplier	Prepayment rate scaling factor	Not applicable if 0% prepayment rate	All factors set to 1.0
Default Assumption	"Reinvestment vector" used to model new loans	When original collateral matures before the reinvestment period ends, the system will automatically assume reinvestment of principal proceeds, subject to constraints defined in the deal	Per-year default and recovery rates are derived from the collateral modeling results
Price Constraints	Minimum purchase price	Minimum prices (e.g., 90–95%) limit aggressive risk-taking	Not modeled
Market Price Adjustment	Market price adjustment	Adjustment to reflect actual purchase price; -2% indicates that assets are bought at 98 instead of 100	0%
Collateral Liquidation Price	Collateral liquidation price, % of par	Collateral Liquidation Price refers to the assumed recovery price (as % of par) for the collateral pool if the CLO enters an early liquidation scenario, such as: 1) An event of default; 2) A failure of a key test (OC, IC); 3) A deal wind-down triggered by equity holders or manager resignation	No early liquidation