National Association of Insurance Commissioners

Date: 2/11/21

LIFE RISK-BASED CAPITAL (E) WORKING GROUP
Thursday, February 11, 2021
12:00 p.m. ET / 11:00 a.m. CT / 10:00 a.m. MT / 9:00 a.m. PT

ROLL CALL

Philip Barlow, Chair	District of Columbia	John Robinson	Minnesota
Steve Ostlund	Alabama	William Leung	Missouri
Thomas Reedy	California	Rhonda Ahrens	Nebraska
Deborah Batista/Eric Unger	Colorado	Seong-min Eom	New Jersey
Wanchin Chou	Connecticut	Bill Carmello	New York
Sean Collins	Florida	Andy Schallhorn	Oklahoma
Vincent Tsang	Illinois	Mike Boerner	Texas
Mike Yanacheak/Carrie Mears	Iowa	Tomasz Serbinowski	Utah

NAIC Support Staff: Dave Fleming

AGENDA

1. Discuss the Moody's Analytics Report on Bonds—*Philip Barlow (DC)* Attachment 1

2. Discuss Request for Mortgage Reporting Guidance Update—*Philip Barlow (DC*)

   - American Council of Life Insurer's (ACLI)/Mortgage Bankers Association (MBA) Request Attachment 2
   - Modification of Original Guidance Document Attachment 3
   - Modification as a New Document Attachment 4

3. Discuss Any Other Matters Brought Before the Working Group—*Philip Barlow (DC)*

4. Adjournment

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MOODY'S ANALYTICS

February 2021

Assessment of the Proposed Revisions to the RBC C1 Bond Factors

Prepared for NAIC National Association of Insurance Commissioners *and the* ACLI Financial Security for Life

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Moody's Investors Service (MIS) provides investors with a comprehensive view of global debt markets through credit ratings and research. Moody's Analytics provides data, analytics, and insights to equip leaders of financial, non-financial, and government organizations with effective tools to understand a range of risks.

Throughout this document, "Moody's" rating refers to an MIS rating. And while this report references MIS, it is written by and reflects the views and opinions solely of Moody's Analytics.

Table of Contents

1 Executive Summary

This report follows in response to the awarded request for proposal (RFP) put forth on October 22, 2020 by the American Council of Life Insurers (ACLI) in conjunction with the National Association of Insurance Commissioners (NAIC). We document Moody's Analytics objective assessment of the proposal for updating RBC C1 bond factors (the C1 Factor Proposal), including the modeling process, the development of assumptions from underlying experience, and related adjustments to reflect the diversification of individual company portfolios used in investment risk factors for fixed income assets, as documented in the Model Construction and Development of RBC Factors for Fixed Income Securities for the NAIC's Life Risk-Based Capital (RBC) Formula, by the American Academy of Actuaries (the Academy) C1 Work Group (American Academy of Actuaries, 2015), under the instruction of the NAIC's Life RBC Work Group.[1]

In addition to providing a comprehensive review of the underlying data, assumptions, methodologies, their resulting potential biases, and their materiality, this report provides a set of practical recommendations to better quantify the identified risks intended to be captured by the RBC C1 bond factors (C1 factors). We recognize that the C1 factors, and thus the models that underpin those factors, can impact business decisions, which ultimately impact solvency. Recommendations will be based on data and modeling approaches recognized as best practice, demonstrate past performance, and rest on sound model risk management guidelines, specifically model validation that includes back-testing and performance benchmarking.[2]

Before proceeding with our recommendations, Moody's Analytics recognizes that the scope of the Academy's work was defined by the NAIC RBC Working Group (the Defined Scope). This report does not, generally, consider the "time, budget and complexity constraints" faced by the Academy in their referenced report *(American Academy of Actuaries, 2015)*. We also recognize that this report does not generally consider the direct or indirect costs of adopting any of the recommendations into the RBC framework and related practicalities. These costs include devoting resources to develop and implement models, data collection, model maintenance, and costs encompassing expertise, governance, and control mechanisms, such as policies and procedures, controls and compliance to ensure proper model use, and implications for organizational structure — at life insurance companies or the NAIC.[3] Rather, as specified in the RFP, this report focuses on the considerations, assumptions, and methodologies used by the C1 Factor Proposal and the extent to which the C1 factors capture the risks outlined above.

With these observations in mind, this report identifies two areas of potential concern that make us question the effectiveness of the proposed C1 factors, considering the possible impact on business decisions and solvency that are further discussed in **Table 1, Table 2,** and **Table 3**.

1. The use of best practices with data and modeling choices. This includes items within the Defined Scope, as well as items outside of the Defined Scope, that Moody's feels are relevant and material. In particular:
   a. The C1 RBC base factors were estimated using an economic state model that does not lend itself to capturing properties and overcoming limitations associated with the default and recovery rate data.
   b. The lack of differentiation across asset classes (corporate, structured, and municipal credit, for example), maturity, and investment income offsets.
   c. Overly conservative assumption for the risk premium, as well as dated discount rate and tax assumptions.
   d. The use of construction of representative portfolios and the separate analysis of each rating category.
   e. The use of multiple NRSROs given their comparability.
   f. Lack of consideration of climate hazards or emerging risks (e.g., pandemic or cyber) that may not be explicitly incorporated into NRSRO ratings and may not be reflected in the historical data used in estimating C1 factors.
2. Model documentation, including model validation and limitations and general prudent model risk management. This is critical for ongoing model monitoring and model updates. With limited articulation of model limitations, the potential for distorted business use and implications for solvency warrants further investigation into the proposed factors. The lack

[1] In addition, this report relies on supporting documentation of the development of assumptions and modeling processes, updated recommendations (American Academy of Actuaries, 2017), and stakeholder feedback.
[2] While (American Academy of Actuaries, 2015) contains Appendix G – Model Validation, Moody's Analytics is not aware of a report that provides a comprehensive assessments of model performance against historic losses or benchmarks.
[3] For guidance on sound model risk management, please see (Board of Governors of the Federal Reserve System and Office of the Comptroller of the Currency , 2011) and references therein.

of documentation and validation related to the portfolio adjustment function and its material impact on C1 factors stands out in particular.

Moody's Analytics is aware of the significant effort involved in creating a broader redesign of the C1 factors. Thus, we suggest phasing-in model development and implementation, data collection, model maintenance, and governance processes. Given the tight April 2021 deadline, Moody's Analytics suggests a Phase 1 redesign that focuses on the portfolio adjustment function and the "slope" of charges across credit ratings (addressing a number of the inputs and elements of the modeling discussed in this report), adhering to the model risk management practices referenced in this report. In addition, Phase 1 should include an articulation of model limitations related to the other items referenced in this document at a level of detail and adhering to a timeline to be determined jointly with stakeholders. Phase 2 would address items that require a longer timeline and would be determined jointly with stakeholders. While we do not expect completion of Phase 2 in 2021, Moody's suggests starting Phase 2 as soon as practical, prior to completion of Phase 1, recognizing the lead time needed for data collection and research. We discuss further details at the end of this document.

Table 1 and **Table 2** present the Summary of Moody's Analytics Significant Areas of Review and Recommendations of key inputs and of the modeling framework that cover Moody's Analytics understanding of the Defined Scope. The recommendations reflect the evolution of new data and techniques that can better describe credit risk since the original C1 factors released in 1992. The recommendations also reflect the increase in size and complexity of life insurance exposure to credit and, therefore, credit risk — in lock-step with credit markets themselves. [4] The recommendations are also influenced by how other regulators, globally, have continued adopting new guidelines to better manage the risks related to growth in credit markets, with an eye toward regulatory arbitrage that is recognized to potentially distort business decisions and solvency.[5] The recommendations recognize constraints that are cited in the C1 Proposal (American Academy of Actuaries, 2015): (1) RBC must be an auditable value, calculated from published financial statements; (2) the C1 component must be based on the credit ratings reported in the NAIC Annual Statement; and (3) the C1 component must represent the statistical safety level prescribed by the NAIC. Essentially, the recommended C1 factors have been developed using a similar methodology to the current factors. Moreover, no single improvement should be made in isolation without consideration of the overall implications of the change, recognizing the overall objectives of C1 factors and potential implications for business decisions that can ultimately impact solvency. Moody's arrived at these conclusions objectively and independently.

Table 1: Summary of Moody's Analytics Significant Areas of Review and Recommendations of Key Inputs

Default Rates	The methodologies used by the C1 Factor Proposal to construct default rates across ratings, as well as methodologies used in differentiating default rates across expansion and contraction states, face data limitation challenges. Moody's recommends updating the methodologies and using additional data referenced in the review that have been demonstrated to better capture credit dynamics.
Recovery Rates	The C1 Factor Proposal's method used to recognize the recovery date does not align with the date of default. This deviation can result in bias with recovery rate levels, as well as their relationships with default rates. Moody's recommends exploring the use of more accurate data and groups when describing recovery distributions and utilizing more current techniques that link recovery with the credit environment.
Discount Rate	Since the modeling work was conducted by Academy in 2015, the discount rate used in the model is calculated using historic data that does not reflect the current low-interest environment, nor the expected continuation of a low interest rate environment. Moody's Analytics recommends updating the discount rate to include December 31, 2013 – December 31, 2020 data to better reflect the current and expected interest rate environment, in conjunction with updated tax assumptions that reflect the 2017 Tax Act.
Construction of the Representative Portfolio	The segmentation and filtering of the sample portfolios used to construct the representative portfolio lack economic justification or sensitivity analysis. For example, for reasons not explained, only NAIC1 and NAIC2 rated issuers are used to determine the number of bonds in the representative portfolio for all rating categories. In addition, each representative portfolio ultimately used in the simulation contains one rating category, which makes the final C1 factors heavily dependent on portfolio adjustment factors. Given the importance of the representative portfolio, we recommend more comprehensive documentation and

[4] In 1992, structured assets were few (outside RMBS), the corporate credit market was on the order of one seventh of what it has been in recent years (Rennison, 2020); life insurers generally hold ~35-50% of corporate issuance (OECD Capital Markets Group, 2020).

[5] For a discussion that explores aligning economic risks and regulatory capital as well as regulatory arbitrage, please see (Basel Committee on Banking Supervision, 2013). For empirical analysis exploring evidence and impact of regulatory arbitrage in European banking and the Financial Crisis, see (Beltrattiab & Paladinocd, 2016). For empirical analysis exploring the evidence of regulatory arbitrage and its impact on overall default risk of banks for the Supplementary Leverage Ratio requirements (the U.S. implementation of the Basel III Tier 1 leverage ratio), see (Federal Reserve Bank of New York, 2019).

	robustness tests that can show whether the segmentation and filtering method has material impact on the C1 factors and explore the option of constructing a representative portfolio that contains all rating categories.
Tax Assumptions	The U.S. corporate tax rate was lowered from 35% to 21% in accordance with the 2017 Tax Reconciliation Act (Deloitte, 2018). Net capital gains included in the taxable income are subject to the 21% rule (CCH Group, 2019). While the model was developed based on historical data before the tax cut, the RBC factors, if adopted, will be applied to insurers, which will pay the updated tax rate. It will be worthy to consider updating the assumed 35% tax rate to 21%. Moody's recommends analysis reflecting the current tax environment.

Table 2: Summary of Moody's Analytics Significant Areas of Review and Recommendations of Modeling Framework

Economic State Model	We have three main concerns regarding the economic state model, which are closely related to the discussion in Section 3.1. First, the two-state model does not accurately capture persistency in default and recovery rates across the credit cycle. Second, the economic state of Loss Given Default (LGD) appears to be mistakenly disconnected from that of default rate for ratings Baa-Caa. Third, the scaling factor used in differentiating default rates across expansions and contractions appears to be overly punitive for the investment-grade segment compared with historical patterns. Moody's recommends a more holistic review of the choice of a framework that can address broader sets of issues, including more precise differentiation across asset classes, as discussed in other sections.
Portfolio Adjustment Factors	The portfolio adjustment factor is one of the most important elements of the model, as it ultimately determines the general RBC level for individual insurers. Unfortunately, documentation is limited, making it difficult to access the materiality of some of the modeling choices. In addition, the limited documentation available suggests a potential material gap between the calculated C1 factor and its target level for individual insurers, especially smaller ones. Moody's recommends: (1) more detailed documentation of the adjustment factor and the underlying economic justification, in conjunction with the doubling of C1 factors for the top-10 largest issuers; (2) further exploring the data and methods used to estimate the portfolio adjustment factors, to ensure they are effective for corporate as well as non-corporate issuers, (3) design the factors to align incentives with the economic risks, and (4) design a structure that brings together the portfolio adjustment factors along with the doubling of C1 of the 10 largest issuers.
Risk Premium	The current assumption of setting the Risk Premium equal to expected loss appears to be overly conservative. While the C1 Factor Proposal recognizes the inconsistency, they point out that the 1992 guidelines defined the Risk Premium in this way and, in conjunction with other parameters, some of which (e.g., AVR) are beyond the scope of this report. While Moody's appreciates the desire to incorporate conservativeness into assumptions, inputs for which accurate proxies are available should be directly used, and rather incorporate the conservative overlay into the final steps to facilitate model transparency. Moody's recommends a broader evaluation of the various interconnected modeling decisions that lead to setting the Risk Premium at the expected loss level, and aligning the models with a general consensus across the actuarial community, including setting the Risk Premium at a one standard deviation loss.

In reviewing the C1 Proposal, Moody's Analytics found several aspects to the underlying modeling and data that were outside of the Defined Scope worth incorporating into this report, included in **Table 3**.

Table 3: Summary of Moody's Analytics Significant Areas of Review and Recommendations of Elements Outside of the Defined Scope

Applicability of Moody's Rated Corporate Data to Other Asset Classes	C1 RBC base factors were developed using Moody's default rate data on Moody's rated public corporate bonds (this report, as well as references herein, uses public corporate and Moody's rated corporate interchangeably) supplemented with S&P's recovery data. After controlling for ratings, we find material differences in observed default, migration, and recovery dynamics across asset classes. These differences question the effectiveness of using public corporate bond data for all asset classes. Moody's Analytics recommends evaluating the possibility of estimating distinct C1 factors using asset-class specific data. For private placements, in particular, Moody's recommends exploring a centralized collection of default, migration, and recovery data that can later be used in further estimating distinct C1 factors and for other purposes.
Simulation and Correlation	The current C1 factor model does not account for variation in cross-industry and cross-asset class concentration risks nor diversification that may be different across life companies' portfolios. These variations can be material, and we recommend additional analysis that assesses the materiality of abstracting from cross-industry and cross-asset class differentiation.

Maturity Effect on Capital Factors	The C1 factors do not differentiate risk across maturity. This can create a material distorted incentive to hold longer-dated bonds whose credit risk is more sensitive to the credit environment. Moody's recommends exploring a maturity adjustment to the C1 factors.
Investment Income Offsets	While investment income can be used to offset loss and support statutory surplus, the C1 factors are modeled with the implicit assumption that all investment profits are fully distributed to policyholders or used to absorb product or operational losses. This introduces a potential bias in differentiating investment income across assets, across rating categories, and across asset classes. Accounting for such heterogeneity in investment income can potentially lead to substantial differences in RBC factors across ratings and asset classes. Moody's recommends more accurately differentiating investment income across assets in the C1 factors.
Comparability Across NRSROs	The model is developed using Moody's rating only. However, NAIC rating designations are often determined by a set of NRSROs ratings. NRSROs have unique differences in credit rating methodologies and do not provide correspondence because they base their credit ratings on a range of qualitative, as well as quantitative, factors. This creates a challenge when mapping ratings across NRSROs to the various NAIC rating designations. It is plausible that the properties (such as default rate, recovery, etc.) of the NAIC rating in practice are substantially different from those of Moody's rating used in the model development. With this in mind, we recommend an assessment of variation across NRSROs rating migration, default, and recovery rates, and across the credit cycle. If this is not possible because of, say, lack of historical data, Moody's Analytics recommends revisiting the use of the second-lowest NRSROs rating in assigning the NAIC designation.
Climate Hazards and Emerging Risks	The C1 factors do not explicitly consider climate hazards or emerging risks (e.g., pandemic or cyber). These risks may not be explicitly incorporated into NRSRO ratings and may not be reflected in the historical data used in estimating the C1 factors. While climate hazards are particularly relevant for the likes of real estate and municipal credit, growing evidence suggests climate hazards and other emerging risks can be material for corporate credit. Moody's Analytics recommends exploring the potential impact of climate hazards and emerging risks on C1 factors across asset classes.

The remainder of this report is organized as follows:

» Section 2 provides Moody's Analytics' general understanding of the C1 factor proposed model.
» Section 3 reviews the key model inputs.
» Section 4 reviews the different model components.
» Section 5 reviews model elements outside the Defined Scope.
» Section 6 concludes and suggests next steps.

It is important to note that Moody's Analytics does not have access to the C1 Factor Proposal's model, data, or final comprehensive technical documentation. Moreover, there have been multiple revisions to the proposed C1 factors. Moody's Analytics has obtained the ACLI model rebuild, which closely replicates the published C1 factors. This rebuild does not include key elements such as the portfolio concentration adjustment or the model that assigns RMBS/CMBS NAIC ratings. While structured asset rating designations are out of scope in this report, we do opine on the effectiveness of corporate factor use. The ACLI's replicated model and the C1 Factor Proposal's methodology papers, along with written communications between the two institutions, were used to review and assess the modeling approach and assumptions. The recommendations and proposals that follow are based on Moody's Analytics' best understanding of the current proposal.

2 General Description of the C1 RBC Proposed Model

The NAIC establishes RBC formulas used to identify potentially weakly capitalized insurance companies. RBC establishes a de facto minimum amount of capital to be held by insurers in order to avoid regulatory intervention. This minimum capital amount protects statutory surplus from the fluctuations that reduce statutory surplus, including credit risk, deferral risk, subordination risk, and event risk.[6]

C1 capital provides protection from statutory insolvency due to losses in statutory asset value resulting from bond defaults, common stock depreciation, and other changes associated with investment activity flowing through statutory surplus.

The prevailing C1 factors were implemented and reported in 1994 with reference to 1970–1990 default experiences. The C1 Factor Proposal was revised multiple times during the 2015–2019 period in response to stakeholder feedback. While the proposed C1 factors were developed based on the loss experience of public U.S. corporate bonds, the same set of factors were recommended for all fixed income securities in NAIC's Schedule D, which is used to report long-term bonds and stocks owned, acquired, sold, redeemed, or otherwise disposed of by insurers during a year. RMBS/CMBS securities are generally filed to NAIC Securities Valuation Office (SVO) and assigned NAIC designations through a financial modeling process conducted by the NAIC Structured Securities Group (SSG), subject to limited filing exemptions (NAIC Securities Valuation Office and NAIC Structured Securities Group, 2019). C1 factors are applied to RMBS/CMBS securities based on the NAIC designations. Based on discussions with the ACLI, other structured securities are treated identically as bonds and are not required to go through the NAIC designation process.

C1 capital charges are intended to cover the 96th percentile portfolio loss in excess of those anticipated in the statutory reserve over a 10-year horizon. Statutory reserve is reflected in the capital fund as Risk Premium, which is currently modeled as the level of annual mean loss from default (after tax and considering recoverable tax on default loss) derived from baseline default and recovery rate assumptions. Risk Premiums are assumed to earn 5% pre-tax interest per annum.
Key inputs to the framework are as follows:

1. Baseline default rates are estimated using 1983–2012 default data, sourced from Moody's (Moody's Investors Service, 2013) as referenced in (American Academy of Actuaries, 2015). For each rating, the marginal default rates in Years 1 through 10 are smoothed using a 4th degree polynomial regression to remove noise. Default rates are differentiated across economic states (e.g., expansion or contraction) using a set of estimated scalars.
2. Baseline recovery rates are estimated using recovery data of senior unsecured bonds provided by Standard & Poor's, covering 1987–2012.
3. Representative portfolios for the seven size categories are constructed based on the corporate bond holdings of life insurers provided by NAIC to the Academy. The final representative portfolio size is set as $10–25 billion USD. Issuers' holding amounts are estimated from a sample of actual life insurers' portfolios (see Section 3.4 for details). Note, only the holding amounts of NAIC-1 and NAIC-2 issuers (824 total) in this portfolio are used to determine the holding amount for each bond in the portfolio, for every rating category in the simulation model. In other words, the representative portfolio for each rating category only differs by issuer rating.

With key inputs in hand, the C1 factor for each rating category is calculated separately through simulation methods. It represents the amount of initial funds needed to cover the 96th percentile greatest default loss over 10 years, offset by statutory reserve, proxied through each rating's Risk Premium. The modeling framework relies on the following calculation steps:

1. Simulate annual economic state for 10 years.
2. The default rate for each rating category in each year is determined by applying a leveled economic state scalar to the baseline default rate, adjusting it up or down according to the simulated economic state.
3. Based on the simulated economic state, simulate a random loss given default (LGD) value for each year, from one of the two distributions (from Step 1) corresponding to the economic state.
4. Simulate representative portfolio loss in each year for each rating category based on the default rate, recovery rate, and the assumptions on Risk Premium and tax, etc. Determine the maximum cumulative portfolio loss with consideration of recoverable tax on default loss in the 10-year period.

[6] American Academy of Actuaries Report of the Invested Assets Work Group regarding the C-1 Framework, to the NAIC's Life RBC Work Group, June 2011. http://actuary.org/files/publications/C1_Framework_Report_061011.pdf (American Academy of Actuaries, 2011).

5. Set the base C1 factor for each rating category as the initial fund required on top of Risk Premium to cover the maximum loss at 96th percentile safety level.[7] The values of these factors in the latest proposal are presented in the last column of **Table 4**.
6. Double the C1 factor of the ten largest issuers held across all debt-related asset classes. The initial filter excludes bonds with C1 RBC equal to zero and NAIC-1 bonds. As applicable after the first filter, if a top-ten issuer has NAIC-1 bonds, they are added back. Up to ten bond issuers of a bond portfolio can be subject to the top-ten doubling rule for concentration risk.
7. Apply the base C1 factors on 677 actual life-insurer portfolios to examine the expected capital coverage for a portfolio with different sizes and to determine the corresponding portfolio adjustment factor that results in enough capital for the portfolio at the 96th percentile safety level. **Table 5** presents the final proposed adjustment factors.

Table 4: Base C1 Factor[8]

	Current	August 2015	June 2017	Sept 2017
Aaa	0.40%	0.28%	0.22%	0.31%
Aa1	0.40%	0.43%	0.32%	0.43%
Aa2	0.40%	0.63%	0.44%	0.57%
Aa3	0.40%	0.79%	0.56%	0.72%
A1	0.40%	0.96%	0.68%	0.86%
A2	0.40%	1.13%	0.82%	1.06%
A3	0.40%	1.30%	0.98%	1.24%
Baa1	1.30%	1.49%	1.13%	1.42%
Baa2	1.30%	1.68%	1.32%	1.69%
Baa3	1.30%	2.01%	1.57%	2.00%
Ba1	4.60%	3.55%	2.88%	3.75%
Ba2	4.60%	4.39%	3.74%	4.76%
Ba3	4.60%	5.62%	4.89%	6.16%
B1	10.00%	5.99%	5.07%	6.35%
B2	10.00%	7.86%	6.89%	8.54%
B3	10.00%	10.31%	9.45%	11.82%
Caa1	23.00%	14.45%	13.87%	17.31%
Caa2	23.00%	19.85%	19.02%	23.22%
Caa3	23.00%	29.82%	29.06%	34.11%*

Source: (American Academy of Actuaries, 2017)

Table 5: Portfolio Adjustment Factor

Current PA Formula

	Issuers	Factor
Up to	50	2.50
Next	50	1.30
Next	300	1.00
Over	400	0.90

Recommended PA Formula (September 2017)

	Issuers	Factor
Up to	10	7.80
Next	90	1.75
Next	100	1.00
Next	300	0.80
Over	500	0.75

Source: (American Academy of Actuaries, 2017)

[7] Note, the target percentile for base RBC factors for individual exposure before portfolio adjustment factor has been updated from the 92nd to the 96th percentile. See correspondence by American Academy of Actuaries (2017) for details.
[8] The factor for Caa3 should be capped at the 30% factor for unaffiliated common stock. Under the current RBC scheme, the factor for NAIC 6 bonds in or near default is set equal to the base factor for unaffiliated common stock (American Academy of Actuaries, 2017).

The following sections examine the various input and methodology steps, exploring the underlying assumptions, potential biases, and materiality, along with recommendations. Section 3 focuses on key inputs. Section 4 explores the modeling framework.

3 Key Inputs to the Framework

This section reviews the key inputs used in the C1 RBC proposed model. We explore the underlying data, along with the assumptions and methodologies, potential biases, and materiality, along with recommendations. This section is organized as follows: Section 3.1 explores the baseline default rates, Section 3.2 explores LGD, Section 3.3 explores the discount rate, Section 3.4 explores the construction of the representative portfolio, and Section 3.5 explores the tax assumptions.

3.1 Default Rates

This section explores the cohort methodology and data used in estimating baseline default rates, as well as the path-dependent behavior of ratings and associated default rates.[9]

3.1.1 Summary of Moody's Analytics Significant Areas of Review and Recommendations

The methodologies used in the C1 Factor Proposal to construct default rates across ratings, as well as methodologies used in differentiating default rates across expansion and contraction states, face data limitation challenges. Moody's recommends updating the methodologies and using additional data referenced in the review that have been demonstrated to better capture credit dynamics.

3.1.2 Review and Analysis Performed by Moody's Analytics

The C1 Factor Proposal takes a cohort approach, whereby all bonds of a given rating, as of a given start date, are kept track of over time. For example, all A2-rated bonds on January 1, 1995 make up a cohort. Experience for each cohort is measured over the following calendar years without considering any rating change subsequent to the cohort start date.

For each rating, the C1 Factor Proposal smoothed the recommended default rate using a 4th degree polynomial regression to remove noise as presented in **Table 6**. The C1 Factor Proposal noted, "In analyzing the raw Moody's cohort data, issues with data credibility were observed in cells with scarce data. Therefore, a smoothing technique was applied to create smooth probability of default curves across ratings and experience years."

Table 6: Smoothed (Across Ratings) Spot Default Rates-4th Degree, based on 2012 Moody's Study

Rating	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9	Year 10
Aaa	0.0006%	0.0035%	0.0003%	0.0429%	0.0353%	0.0331%	0.0276%	0.0276%	0.0276%	0.0276%
Aa1	0.0019%	0.0093%	0.0081%	0.1006%	0.0694%	0.0575%	0.0459%	0.0459%	0.0459%	0.0459%
Aa2	0.0060%	0.0205%	0.0334%	0.1778%	0.1132%	0.0883%	0.0714%	0.0714%	0.0714%	0.0714%
Aa3	0.0152%	0.0401%	0.0853%	0.2503%	0.1628%	0.1277%	0.1085%	0.1149%	0.1147%	0.1302%
A1	0.0321%	0.0714%	0.1617%	0.2958%	0.2166%	0.1798%	0.1621%	0.1909%	0.1930%	0.2192%
A2	0.0587%	0.1186%	0.2475%	0.3102%	0.2759%	0.2485%	0.2364%	0.2788%	0.2810%	0.3160%
A3	0.0963%	0.1866%	0.3237%	0.3065%	0.3444%	0.3374%	0.3348%	0.3761%	0.3744%	0.4137%
Baa1	0.1463%	0.2813%	0.3777%	0.3050%	0.4280%	0.4516%	0.4613%	0.4853%	0.4750%	0.5119%
Baa2	0.2115%	0.4094%	0.4078%	0.3258%	0.5357%	0.5994%	0.6233%	0.6139%	0.5906%	0.6172%
Baa3	0.2980%	0.5802%	0.4224%	0.3876%	0.6810%	0.7939%	0.8316%	0.7749%	0.7352%	0.7424%

Source: (American Academy of Actuaries, 2015)

Two aspects of the approach warrant further exploration. First, the fundamental limitations of the data, as it relates to the framework, i.e., statistical properties of the data (e.g., path-dependent behavior) and the number of observations per rating category. Second, the use of the cohort approach.

We begin with an observation (Moody's Investors Service, 2020 (1)): Moody's credit ratings are opinions of ordinal, horizon-free credit risk and, as such, do not target specific default rates or expected loss rates. Moody's believes the needs of market

[9] The term "path-dependent," recognizes the history of a bond's rating as well as its current rating affects the bond's future rating state and migration. For example, a bond that has experienced a recent rating action may be less likely to experience an additional rating action in the immediate future, when compared to an otherwise identical bond. An equivalent term, non-Markovian, is often also used in references herein.

participants are best served by ratings that are assessments of relative credit risk rather than cardinal risk measures. Indeed, rating transitions are path-dependent. By the same logic, neither are migrations implicit in the cohort default rates term structures. Thus, one should recognize that using ratings data in this way does not consider potentially material time-series dynamics.

While the use of a cohort approach is legitimate in principle, limitations must be understood. Limitations cited by authors of the C1 Factor Proposal with the number of observations per rating category and noted challenges with subsets of data, such as the change in ratings methodology in the financial sector after the financial crisis in 2008–2009, are well recognized (Moody's Investors Service, 2020 (1)). While the C1 Factor Proposal recommends the smoothing method that best fits the original data, it is not clear if this chosen performance criteria makes sense in light of the data limitations (i.e., statistical properties and number of observations). Fitting a smoothing function on noisy data can often lead to a poor description of reality. This issue is exacerbated by poor statistical properties, including the path-dependent nature of default rates.

The C1 Factor Proposal recognizes this point when considering combining transition tables with default rates while incorporating credit migration. However, they also cited the observed and legitimate challenge that the progression of ratings transition for a bond is path-dependent. This challenge is prevalent in the cohort approach as well. We return to path-dependency related issues later in this section.

While challenges abound, we transition to an alternative point of reference. Moody's Idealized Default Rates, presented in Table 7, provide a benchmark for default rates across ratings. This was independently suggested by ACLI technical experts based on interviews.[10]

Table 7: Moody's idealized annual spot expected default rates used as benchmark default probability rates in Moody's rating models

Rating	1-Year	2-Year	3-Year	4-Year	5-Year	6-Year	7-Year	8-Year	9-Year	10-Year
Aaa	0.0001%	0.0001%	0.0005%	0.0011%	0.0011%	0.0011%	0.0012%	0.0014%	0.0016%	0.0018%
Aa1	0.0006%	0.0024%	0.0070%	0.0110%	0.0100%	0.0110%	0.0120%	0.0130%	0.0150%	0.0180%
Aa2	0.0014%	0.0066%	0.0180%	0.0210%	0.0210%	0.0210%	0.0220%	0.0240%	0.0290%	0.0361%
Aa3	0.0030%	0.0160%	0.0400%	0.0420%	0.0410%	0.0411%	0.0441%	0.0451%	0.0552%	0.0732%
A1	0.0058%	0.0312%	0.0800%	0.0721%	0.0721%	0.0692%	0.0763%	0.0743%	0.0934%	0.1277%
A2	0.0109%	0.0591%	0.1521%	0.1233%	0.1224%	0.1165%	0.1277%	0.1199%	0.1543%	0.2202%
A3	0.0389%	0.1111%	0.2103%	0.1807%	0.1910%	0.1813%	0.2018%	0.1921%	0.2229%	0.2843%
Baa1	0.0900%	0.1902%	0.2808%	0.2715%	0.2723%	0.2730%	0.3042%	0.3051%	0.3060%	0.3377%
Baa2	0.1700%	0.3005%	0.3617%	0.3731%	0.3846%	0.3963%	0.4488%	0.4509%	0.4014%	0.3721%
Baa3	0.4200%	0.6327%	0.6670%	0.6817%	0.6863%	0.6704%	0.6542%	0.6690%	0.6314%	0.5613%
Ba1	0.8700%	1.1601%	1.1329%	1.1046%	1.1273%	1.0241%	0.8640%	0.8930%	0.8685%	0.7776%
Ba2	1.5600%	1.9403%	1.7715%	1.7085%	1.7275%	1.4849%	1.0307%	1.0750%	1.1207%	0.9731%
Ba3	2.8100%	2.7781%	2.4976%	2.0840%	2.2946%	1.8493%	1.3062%	1.2766%	1.1864%	1.1406%
B1	4.6800%	3.8817%	3.4927%	2.5673%	2.6349%	2.1102%	1.5102%	1.3602%	1.2661%	1.2189%
B2	7.1600%	4.8578%	4.3926%	3.0551%	3.1513%	2.4467%	1.7582%	1.5002%	1.4295%	1.3283%
B3	11.6200%	5.6461%	5.3004%	3.8116%	3.9626%	2.9472%	2.5424%	2.2899%	1.7799%	1.6913%

Source: Moody's Investor Service updated October 25, 2018, represented as Year *n* Annual Spot = (Year *n* Cumulative - Year *n-1* Cumulative)/(1-Year *n-1* Cumulative)

Before proceeding, it is important to understand the purpose and use of Moody's Idealized Default Rates that have remained unchanged since 1989. Per the most recent Rating Symbols and Definition (Moody's Investors Service, 2020 (1)):

> To rate some obligations in some asset classes, however, Moody's uses models and tools that require ratings to be associated with cardinal default rates, expected loss rates, and internal rates of return in order for those models and tools to generate outputs that can be considered in the rating process. For these purposes, Moody's has established a fixed common set of default rates, expected loss rates, and internal rates of return that vary by rating category and/or investment horizon (Moody's Idealized

[10] The question of applicability of the corporate data for other asset classes is discussed in Section 5.1.

Default and Expected Loss Rates;[11] hereafter called "Moody's Idealized Rates"). By using a common fixed set of benchmark parameters, rating models are more likely to provide consistency with respect to the estimation of relative risk across rating levels and investment horizons and can be more easily compared to one another. Moody's Idealized Rates are used with other tools and assumptions that have a combined effect on model outcomes. While cardinal measures are used as inputs to models, the performance of ratings is benchmarked against other metrics.[12] Although Moody's Idealized Rates bore some degree of relationship to corporate default and loss experience at the time they were created, that relationship has varied over time, and Moody's continuing use of the Idealized Rates for modeling purposes does not depend on the strength of that relationship over any particular time horizon. When we perceive changes in risk that necessitate changes in our credit analysis, we make revisions to key assumptions and other aspects of models and tools rather than changing this fixed common set of benchmark parameters. This approach enables us to make adjustments that only affect the particular sectors and asset classes we expect will experience significant changes in risk at a given time.

A casual comparison across the two-term structures highlights important differences. For example, monotonically increasing spot rates for the high-grade universe is commonly recognized as high-quality credit that is more likely to deteriorate than improve; this condition is not met with the recommended baseline term structure. With this, we do recognize that the Idealized Default Rates are not intended to match historical or future ratings performance.

Next, we consider modeling default rates across contraction and expansion economic states, closely related to path-dependency issues with the data. We apply a distinct, single multiplier to each rating baseline default rate. While, in spirit, the approach makes sense, practicalities do not lend themselves in describing the tendencies for the default rate term structure to tilt and become upward (or less downward) sloping during a benign environment and more downward (or less upward sloping) during a deteriorated environment (Beygi, Makarov, Zhao, & Dwyer, 2016). Section 4.1 further discusses the challenges associated with the economic state framework.

With these factors in mind, material improvements in techniques and data availability have been made, allowing more accurate capturing of nuanced time series dynamics for rating migration and default across credit environments that address the observed path-dependent behavior of ratings. These approaches are used in practice by a wide range of institutions, as documented in a number of methodology papers by Moody's (Moody's Analytics, 2020) and others, such as (Lando & Skødeberg, 2002) and (Aguais, Forest, & Wong). Moody's Analytics recommends exploring these approaches. Section 4.1 further discusses the economic state model.

3.2 Recovery Rates

3.2.1 Summary of Moody's Analytics Significant Areas of Review and Recommendations

The method used by the C1 Factor Proposal to recognize the recovery date does not align with the date of default. This deviation can result in bias with recovery rate levels, as well as their relationships with default rates. Moody's Analytics recommends exploring the use of more accurate data and groups when describing LGD distributions and utilizing more current techniques that link recovery with the credit environment.

3.2.2 Review and Analysis Performed by Moody's Analytics

The C1 Factor Proposal estimates two empirical distributions of LGD, for economic contraction and expansion, respectively, using historical data. Each LGD distribution consists of 11 buckets, <0, 0-10%, 10-20%, etc., each with an average LGD and probability of occurrence. Negative LGD corresponds to recovery greater than par value (American Academy of Actuaries, 2015). For example, to construct the LGD distribution for a contraction state, the bond-level LGD data in the contraction period 1983–2012 are grouped into the aforementioned 11 buckets first. Then, the relative frequencies of LGD data points are used as the probability of

[11] These tables are highly stylized and are not intended to match historical or future ratings performance. The tables were constructed in 1989 with reference to corporate default and loss experience over four historical data points. In particular, the 10-year idealized default rates for A2, Baa2, Ba2, and B2 were set equal to the 10-year historical default rates for corporate issuers with single A, Baa, Ba, and single B ratings, as observed between 1970 and 1989. In contrast, the 10-year idealized default rates for Aaa and Aa2 were set lower than their historical default rates. All the other idealized default rates — for different alphanumeric ratings and at different rating horizons — were derived through interpolation, rather than being matched to historical data. The idealized expected loss table was then derived by multiplying each element of the idealized default table by an average loss severity assumption, set equal to the approximate historical recovery rate of senior unsecured debt observed between 1970 and 1989. Moody's has not published a revised version of these tables since the 1989 version and has no plans to revise them at the time of this writing.

[12] Moody's approach to measuring ratings performance is discussed in "Measuring the Performance of Credit Ratings" (Moody's Special Comment, November 2011).

each bucket. For each simulation trial, the proposed model randomly chooses an LGD bucket using the probability of occurrence for each bucket, and then uses the average LGD of the selected bucket to compute loss.

Data used to develop the LGD distribution is based on senior unsecured bond data provided by Standard & Poor's, covering 1987–2012. The average LGD is 53.1% among 1,260 bonds. The detailed LGD data collected from S&P has not been disclosed to either ACLI or Moody's Analytics. ACLI attempted to re-construct the LGD distributions using Moody's recovery data and managed to obtain similar, average LGD (53.1%) and sample size (1,257 bonds). Furthermore, the LGD distributions replicated by ACLI were used in the portfolio loss simulation and resulted in nearly-identical RBC factors for all ratings except Caa3. Therefore, we use ACLI's replication methods for evaluation.

We make three observations regarding the data and the methods by which the data are used to paramterize the economic state model.

First, the C1 Factor Proposal used bond-level recovery data to estimate the empirical LGD distribution. The C1 Factor Proposal recognized that "recovery rates are provided by the issuer, not by issue" but argued that "because the LGD by issuer rating are stable, it is reasonable to assume that the variability in recovery would be observed at the issue level" (American Academy of Actuaries, 2015). Based on empirical observations, this data may be influenced by issuers with a large number of bond defaults. The underlying risk factors are largely the same for bonds linked to the same issuers. For example, 49 senior unsecured bonds from Pacific Gas & Electric (PG&E) defaulted, all with zero LGD in 2001, one of the four contraction years. The estimated LGD distribution for economic contraction will, therefore, be influenced heavily by PG&E bond defaults. We can address this issue using principal-weighted LGD by issuers first and then using the average of issuer LGDs.

Second, Moody's Analytics' recovery data provides up to three alternative methods for deriving LGD, depending on data availability. For each defaulted bond, the LGDs from the three methods can differ. Moody's Ultimate Recovery Database includes a field with Moody's recommended method for each default, based on Moody's extensive experience with recovery data (Moody's Analytics, 2016). While the C1 Factor Proposal used LGD data provided by S&P, it does not clearly define from which method(s) LGD is derived:

» Settlement Method — value of the settlement instruments is taken at or close to default
» Liquidity Method — value of the settlement instruments is taken at the time of a liquidity event
» Trading Price Method — value of the settlement instruments is based on the trading prices of the defaulted instruments at post-emergence

Third, based on the electronic communications between ACLI and the Academy, recovery rate seems to have been categorized by the date of emergence from default rather than the default date (American Council of Life Insurers, 2019). It is not uncommon for the recovery process to take years to complete. The year of emergence is likely to be in a different economic state from the year of default. As a result, the empirical LGD distribution for a contraction economic state may be estimated from defaults that occurred primarily during expansion years. This process is contradictory to the loss simulation model in the C1 Factor Proposal, where loss is realized on the year of default.

With these issues in mind, Moody's Analytics recommends using issuer-level LGD data derived from the more commonly used recovery method and grouped by the year of default to estimate the empirical LGD distributions. More broadly, there have been advances in techniques that allow more accurately linking recovery with the credit environment ((Moody's Analytics, 2011), (Moody's Analytics, 2010 (2)), and that account for correlation between the firm's underlying credit quality and recovery, used in practice that should be considered when modeling LGD dynamics.

3.3 Discount Rate

3.3.1 Summary of Moody's Analytics Significant Areas of Review and Recommendations

Since the modeling work was conducted by Academy in 2015, the discount rate used in the model is calculated using historic data that does not reflect the current low-interest environment, nor the expected continuation of a low interest rate environment. Moody's Analytics recommends updating the discount rate to include December 31, 2013 to December 31, 2020 data to better reflect the current and expected interest rate environment in conjunction with updated tax assumptions that reflect the 2017 Tax Act (see Section 3.5 for details).

3.3.2 Review and Analysis Performed by Moody's Analytics

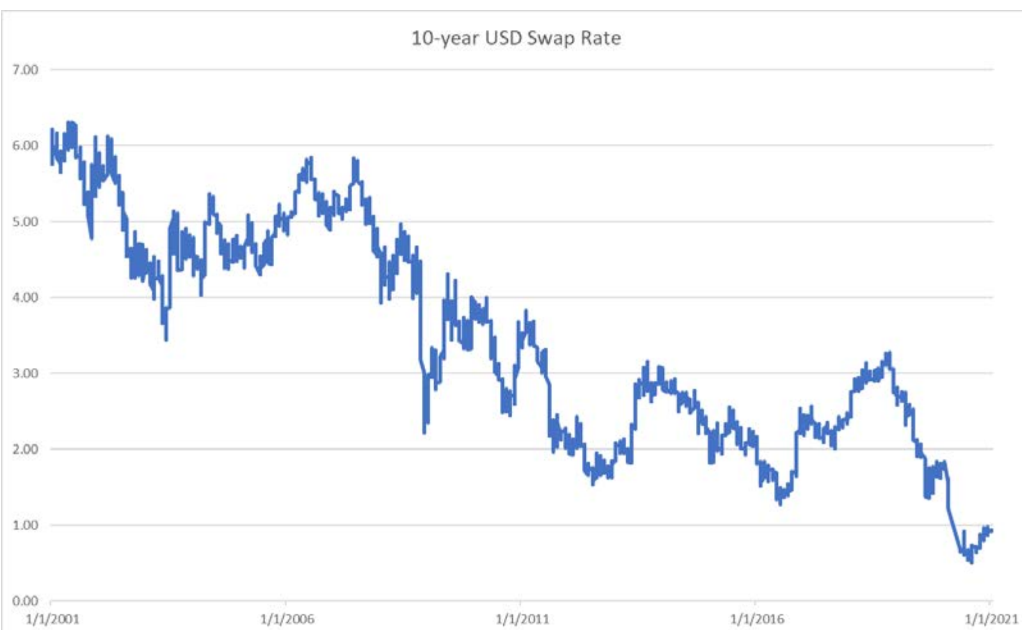
This section evaluates data and methods used in estimating the discount rate. The discount rate used in the C1 Factor Proposal is assumed to be the average ten-year LIBOR swap rate from December 31, 1993 to December 31, 2013, which is 5.02% pre-tax/3.26% after-tax. The numbers are then rounded to 5% pre-tax/3.25% after-tax (American Academy of Actuaries, 2015). If the discount rate is updated through April 30, 2017, the pre-tax rate drops to 4.2%, as documented in the Academy's letter on February 14, 2018 (American Academy of Actuaries, 2018). It is recognized that this time window for the discount rate is chosen since the modeling work was conducted in 2015.

While Moody's Analytics does not have access to the data used in the C1 Factor Proposal, or information about the exact data source, we use the 10-year USD swap rate from the Federal Reserve H.15 Daily Selected Interest Rates Release and Intercontinental Exchange (ICE) in our analysis. ICE data was used starting August 1, 2014, when the Federal Reserve System data series was discontinued.

Figure 1 shows the downward trend in the 10-year USD swap rate over the most recent two decades. The rate is below 3% for most of the 2011–2021 period. Since the Federal Reserve took extensive measures to support the economy during the global pandemic (Federal Reserve, 2020), the rate decreased further, often to under 1%. The November Minutes of the Federal Open Market Committee quotes, "The Committee decided to keep the target range for the federal funds rate at 0–¼% and expects it will be appropriate to maintain this target range until labor market conditions have reached levels consistent with the Committee's assessments of maximum employment and inflation has risen to 2% and is on track to moderately exceed 2% for some time" (the Federal Open Market Committee, 2020). Therefore, it is reasonable to assume that the current low interest rate environment will likely remain for an extended period, considering the 30-year treasury rate sat under 2% at the time we wrote this report.

With these observations in mind, Moody's Analytics recommends updating the discount rate to include December 31, 2013 to December 31, 2020 data to better reflect the current and expected interest rate environment. Please note, the 2017 Tax Act took effect during this time window. Section 3.5 discusses the update to tax assumptions.

Figure 1: 10-Year USD Swap Rate



Source: Federal Reserve System (data prior to August 1, 2014) and Intercontinental Exchange (data on or after August 1, 2014).

3.4 Construction of the Representative Portfolio

3.4.1 Summary of Moody's Analytics Significant Areas of Review and Recommendations

The segmentation and filtering of the sample portfolios used to construct the representative portfolio are not accompanied by economic justification or sensitivity analysis. For example, for reasons not explained, only NAIC1 and NAIC2 rated issuers are used to determine the number of bonds in the representative portfolio for all rating categories. In addition, each representative portfolio ultimately used in the simulation contains one rating category, which makes the final C1 factors heavily dependent on portfolio adjustment factors. Given the importance of the representative portfolio, we recommend more comprehensive documentation and robustness tests that can show whether the segmentation and filtering method has material impact on the C1 factors and explore the option of constructing a representative portfolio that contains all rating categories.

3.4.2 Review and Analysis Performed by Moody's Analytics

Base C1 factors are intended to cover 96th percentile portfolio loss in excess of those anticipated in the statutory reserve over a 10-year horizon. The C1 factors are estimated using simulation methods described in Section 5.2. This section describes the representative portfolio analyzed in the simulation.

The representative portfolio for each rating category consists of bonds with the same initial rating. The number of bonds, as well as the holding amount of each bond in the portfolio, is determined according to the corporate bond holdings as of December 31, 2011, of the entire universe of 782 life insurers (portfolio size range from under $0.5 billion to $80 billion) provided by NAIC to the authors of the C1 Factor Proposal; Moody's Analytics did not have access to these portfolios.[13, 14]

The C1 Factor Proposal constructs the reference portfolio by placing each credit portfolio into seven size categories, shown in **Table 8**. Under the argument that Category 6 "contains the 50% cumulative Book Adjusted Carrying Value (BACV) point with a range of 33%–56% of industry BACV," the C1 Factor Proposal chose the 24 life companies' portfolios in this category to form the basis of the representative portfolio.

Table 8: Life Company Size Categories

Size	$Billion		$Billion	Count
1	0.0	-	0.5	503
2	0.5	-	1.0	54
3	1.0	-	2.5	70
4	2.5	-	5.0	35
5	5.0	-	10.0	32
6	10.0	-	25.0	24
7	25.0	-	80.0	16

Bonds from these 24 portfolios are then ranked by BACV and segmented into 18 groups. Group 1, 2, 17, and 18 each hold 1/32 of the total BACV, while the remaining 14 groups hold 1/16 of BACV. In the final representative portfolio, the initial holding amount of bonds in each group is set to be the average BACV of the corresponding group from the 24 life insurer's portfolio (last column of **Table 9**). The number of bonds in each group, on the other hand, is set to be the average (across 24 insurer's bond portfolios) number of issuers in each group with rating NAIC-1 or NAIC-2. This results in a final representative portfolio with a total of 824 bonds across 18 groups, with each group's total holding amount determined by the last column of **Table 9**.

[13] Bonds guaranteed by the full faith and credit (FFC) of the U.S. government, affiliate bonds and zero value bonds are removed from the sample.
[14] In total, seven representative portfolios are created from life insurers in different size categories; only the portfolio created based on 24 insurers with portfolio size between $10–$25 billion is used in the end.

Table 9: Representative Portfolio

	NAIC Rating					
Bin	**1**	**2**	**3**	**4**	**5**	**$Million**
1	82	76	47	35	8	2.013
2	37	36	15	10	1	5.062
3	56	53	13	6	2	7.789
4	39	42	7	2	1	11.108
5	30	34	5	1	0	14.229
6	25	30	3	1	0	17.209
7	21	26	2	0	0	20.336
8	19	22	2	0	0	23.561
9	16	20	1	0	0	26.895
10	15	17	1	0	0	30.664
11	13	15	1	0	0	34.746
12	13	12	0	0	0	39.485
13	11	11	0	0	0	46.288
14	8	9	0	0	0	55.684
15	8	7	0	0	0	65.445
16	6	6	0	0	0	81.004
17	3	2	0	0	0	95.349
18	3	1	0	0	0	142.017
Issuer Count	405	419	97	55	12	
Coefficient of Variation	1.13	1.00	1.02	0.83	0.77	
Issuer Count %	41%	42%	10%	6%	1%	
Amount %	47%	47%	4%	1%	0%	

While Moody's Analytics understands the objectives and the need to construct a representative portfolio, given the spirit of the framework justifications for various modeling choices and implications were not included in the documents. A few that stand out:

1. It is not clear how the initial seven size categories used to segment life insurers are determined. Given that the definition of the size categories ultimately determines which life insurers' portfolios are used to construct the representative portfolio, there may be a material impact on base C1 factors. It is unclear whether any robustness test was done to examine to what extent the definition of size categories affects the C1 factor.
2. Ultimately, only 24 out of 782 life companies' portfolios are used to construct the representative portfolio. As recognized in the C1 factor Proposal, these 24 portfolios are much larger in size than the industry average. The implication is that the base C1 factors calculated based on the representative portfolio are only applicable to large life companies' portfolios. For smaller insurers, the effectiveness of the C1 factors is almost entirely dependent on the model of portfolio adjustment factors, which lack model documentation and backtesting. Section 4.2 provides a detailed review of the portfolio adjustment factors.
3. It is not clear why the exercise used to count the number of issuers is limited to NAIC-1 and NAIC-2, given representative portfolios are ultimately assigned the same number of bonds across all rating categories. If we include the count of issuers with NAIC-3 and below ratings from the 24 insurers' portfolios, the number of bonds in the final representative portfolio will increase accordingly, which will add diversification and lower the base C1 factor.
4. Each representative portfolio ultimately used in the simulation contains one rating category, which again makes the final C1 factors heavily dependent on portfolio adjustment factors, which we review in Section 4.2.

With these observations in mind, Moody's Analytics recommends providing economic justification for and conducting robustness tests on the definition of life insurers' size categories. Moody's Analytics also recommends exploring a revision to the representative portfolio's construction to include all ratings and possibly asset classes in a single representative portfolio.

3.5 Tax Assumptions

The U.S. corporate tax rate was lowered from 35% to 21%, in accordance with the 2017 Tax Reconciliation Act (Deloitte, 2018). Net capital gains included in the taxable income are subject to the 21% rule (CCH Group, 2019). While the model was developed based on historical data before the tax cut, the RBC factors, if adopted, will be applied to insurers, which will pay the updated tax rate. It will be worthy to consider updating the assumed 35% tax rate to 21%. Moody's recommends analysis reflecting the current tax environment.[15]

4 Modeling Framework

This section reviews the assumptions and methodologies that underpin the modeling framework. Section 4.1 reviews the economic state model, Section 4.2 explores portfolio adjustment factors, and Section 4.3 explores the Risk Premium.

4.1 Economic State Model

4.1.1 Summary of Moody's Analytics Significant Areas of Review and Recommendations

We have three main concerns regarding the economic state model, which are closely related to the discussion in Section 3.1. First, the two-state model does not accurately capture persistency in default and recovery rates across the credit cycle. Second, the economic state of LGD appears to be mistakenly disconnected from that of the default rate for ratings Baa-Caa. Third, the scaling factor used in differentiating default rates across expansions and contractions appears to be overly punitive for the investment-grade segment compared with historical patterns. Moody's recommends a more holistic review for the choice of a framework that can address broader sets of issues, including more precise differentiation across asset classes, as discussed in other sections.

4.1.2 Review and Analysis Performed by Moody's Analytics

To differentiate default rate and recovery rate during economic booms and downturns, the C1 Factor Proposal defines economic states according to the National Bureau of Economic Research's (NBER) economic state classifications across the 1983–2012 period. Years 1991, 2001, 2008, and 2009 are classified as "contraction" years, while the remaining years are classified as "expansion" years. The baseline default rate is scaled up or down using an economic scalar for the economic state.

There are two models in the simulation process, as summarized in **Table 10**:

- The two-state model is used for recovery rates, and Aaa-A default rates, with the economic state in years one through ten drawn independently according to the probability summarized in **Table 12**.
- The four-state model is used for Baa-Caa default rates. It includes continuing expansion and continuing contraction states in addition to expansion and contraction states. The economic state in the first year is drawn from the probability distribution shown in **Table 13**. The states in subsequent years are dependent on the previous year's state and follow the transition probabilities summarized in **Table 14**.

LGD is drawn from two different distributions corresponding to expansion and contraction state, respectively. Section 3.2.2 describes details.

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[15] The 2017 Tax Act repeals the 3-year carryback, 15-year carryforward period for life insurance companies' operations losses. The Act provides that all corporations (including life companies) may carry NOLs forward indefinitely, but limits utilization of NOLs to 80 percent of a given year's taxable income with no loss carryback capacity (Deloitte, 2018).

Table 10: Definition of Two-state and Four-state economic models

Economic model type	Economic state	Description
2-state model	Expansion	Defined by NBER
	Contraction	Defined by NBER. 1991, 2001, 2008, and 2009 are contraction years in the study period of 1983-2012.
4-state model	Continued Expansion	The previous year was an "Expansion" and the present year is also an "Expansion."
	Expansion	The previous year was a "Contraction" and the present year is an "Expansion."
	Contraction	The previous year was an "Expansion" and the present year is a "Contraction."
	Continued Contraction	The previous year was a "Contraction" and the present year is also a "Contraction."

Table 11: Economic models for default rate and recovery rate

Variable	Rating	Economic model
Default rate	Aaa, Aa, A	2-state economic model
	Baa, Ba, B, Caa, C	4-state economic model
Recovery rate	All ratings	2-state economic model

Table 12: Two-state probability distribution

Economic State	Probability
Expansion	86.67%
Contraction	13.33%

Table 13: Four-state probability distribution for the first year

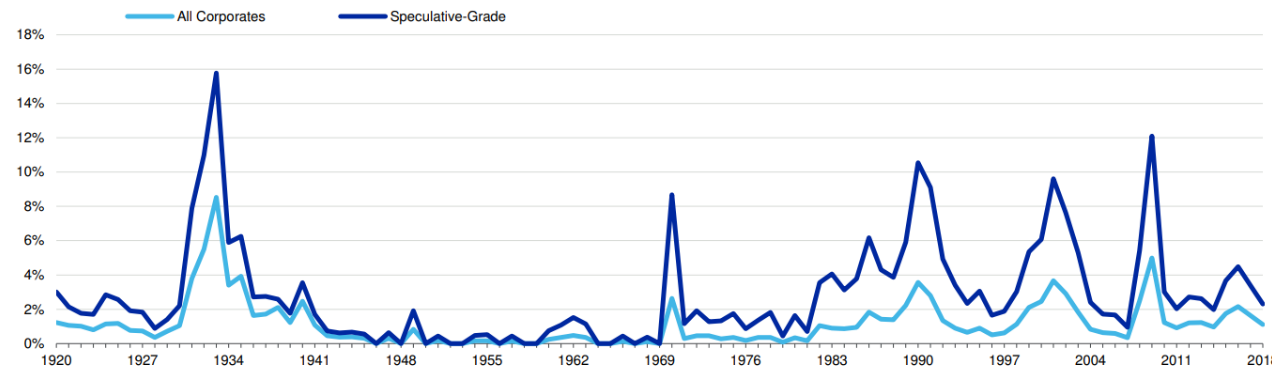
Economic State	Probability in Year 1
Continuing expansion	73.33%
Expansion	13.33%
Contraction	10%
Continuing contraction	3.33%

Table 14: Economic state transition probability for the four-state model

State/Probability	Expansion	Contraction
Expansion	88.00%	12.00%
Contraction	80.00%	20.00%

There are several data treatment and modeling assumptions that may be introducing bias and should be understood. First, the economic state model does not seem to capture serial correlations in defaults. The two-state model assumes the independence of economic states across years. Since default rate is calculated as the baseline default rate multiplied by an economic scalar, default rate is also assumed implicitly to be independent across the years. This assumption does not align with empirical patterns. For example, **Figure 2** demonstrates the persistence in global corporate default rates of years before and after a peak.

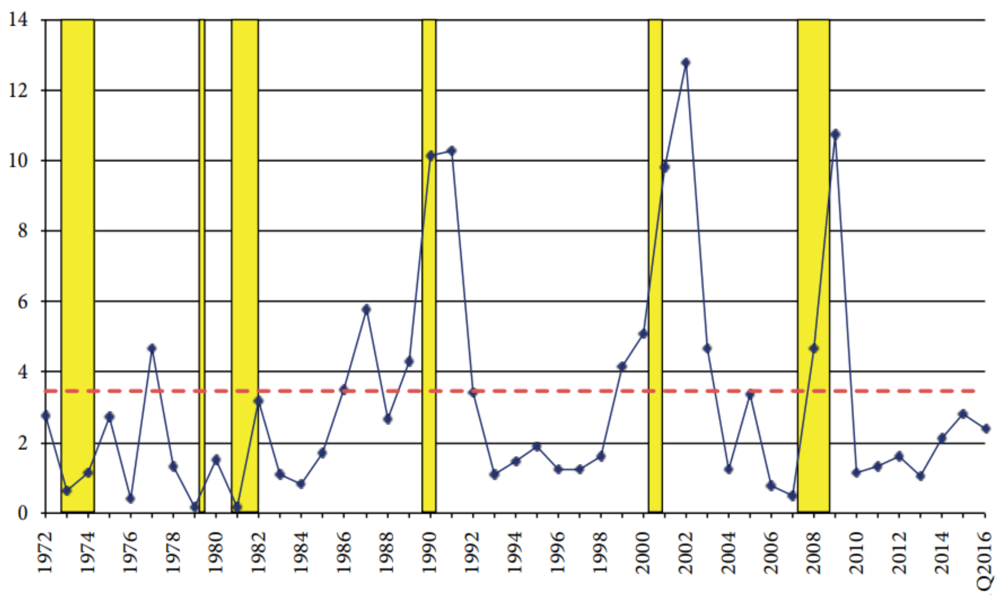
Figure 2: Default rate of global corporate 1920–2018



Source: Moody's Investors Service

While the dependence of economic states across years is established in the four-state model, the model may not be adequately capturing the default rate autocorrelation. The business cycle and the credit cycle do not perfectly overlap. As seen in **Figure 3**, multiple peaks in the U.S. high-yield default rate occurred outside the recession periods (Altman & Kuehne, 2016). It takes time for corporate fundamentals to weaken and reach the default point during a downturn.

Figure 3: Historical default rates of high-yield bonds and recession periods in the United States



Source: (Altman & Kuehne, 2016)

Second, the default rate and recoveries for some ratings are modeled using different economic state scenarios. For Baa1-Caa3, default rate is modeled in the four-state model, while LGD is modeled using a separate two-state model. The ACLI's replicated model is used to simulate the economic scenarios and test this modeling choice. Even if the four-state scenarios are mapped to two-state (for example, map continuing expansion to expansion), 23% of trials have different values from the separate two-state scenarios for LGD modeling. As a result, the default rate may be scaled up by the contraction economic scalar, while LGD is drawn from the distribution for expansion in any simulation trial.

Third, economic scalars used to scale the default rate across states are not adjusted for the remaining time to maturity (Years 1–10), referenced as leveled economic scalars. This approach fails to account for the default rate term structure effect. Specifically, **Table 15** (American Academy of Actuaries, 2015) reports the original economic scalars directly calculated from the empirical data. We can see that the values of these scalar vary significantly across tenors. However, due to data noises, the pattern of these scalars is not always intuitive. Consequently, the C1 Factor Proposal compresses these economic scalars across tenors into a single scalar for each economic state and rating, shown in Table 16 (American Academy of Actuaries, 2015). Taking Baa rating, for example, the leveled economic scalar for the contraction state is around 215%. This percentage is lower than the empirical scalar in Years 9–10 and higher than the empirical scalar in Years 1–8.

The use of leveled economic scalars seems to be, in general, overly punitive for investment-grade issues in early years when the default rates tend to be lower, and not sufficiently punitive in later years when default rates tend to be higher. We expect this will dampen concentrated losses overall, but need to assess the dynamics, along with a review of the base default rate term structure.

Table 15: Economic scalar for Baa rating based on empirical data. Source: (American Academy of Actuaries, 2015)

		Duration 1	Duration 2	Duration 3	Duration 4	Duration 5	Duration 6	Duration 7	Duration 8	Duration 9	Duration 10
Baa	Continued Contraction	463%	188%	253%	155%	255%	300%	234%	412%	440%	390%
	Contraction	170%	144%	162%	188%	180%	191%	209%	200%	246%	329%
	Expansion	126%	121%	96%	145%	140%	123%	112%	81%	64%	78%
	Continued Expansion	69%	87%	84%	77%	73%	70%	71%	65%	55%	55%
	Combined	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%

Table 16: Levelled economic scalars by rating. (American Academy of Actuaries, 2015)

Rating	Continued Contraction	Contraction	Expansion	Continued Expansion
Aaa	274.95%	274.95%	73.65%	73.65%
Aa1	274.09%	274.09%	73.42%	73.42%
Aa2	274.82%	274.82%	73.61%	73.61%
Aa3	273.78%	273.78%	73.34%	73.34%
A1	272.87%	272.87%	73.09%	73.09%
A2	272.14%	272.14%	72.90%	72.90%
A3	272.52%	272.52%	73.00%	73.00%
Baa1	322.31%	214.79%	113.01%	73.81%
Baa2	322.24%	214.75%	112.99%	73.80%
Baa3	322.79%	215.11%	113.18%	73.92%
Ba1	297.28%	194.22%	83.81%	81.89%
Ba2	297.38%	194.29%	83.84%	81.92%
Ba3	297.27%	194.21%	83.81%	81.89%
B1	221.14%	149.58%	119.01%	86.17%
B2	221.22%	149.64%	119.05%	86.20%
B3	221.14%	149.58%	119.01%	86.17%
Caa1	223.88%	180.42%	91.00%	85.49%
Caa2	223.71%	180.28%	90.93%	85.42%
Caa3	223.56%	180.16%	90.87%	85.36%

Given the fundamental nature of the economic state model in generating the factors, as well as potential limitations referenced in prior sections (Section 3.1, Default Rates, in particular, and subsequent sections, Section 5.2, Correlation, in particular), we recommend a more holistic review for a framework choice that can address a broader set of issues and would allow for more precise differentiation across asset classes and also more accurately capture issues related to the time-series dynamics discussed here.

In particular, and, as discussed in Section 3.1 and references therein, there have been material improvements in techniques and data availability to more accurately capture nuanced time series dynamics for rating migration and default across credit environments that address the observed path-dependency behavior of ratings, and more accurately model correlated recovery dynamics. These approaches are used in practice for a wide range of related applications and at a wide range of organization types. Moody's Analytics recommends exploring these approaches.

4.2 Portfolio Adjustment Factors

4.2.1 Summary of Moody's Analytics Significant Areas of Review and Recommendations

The portfolio adjustment factor is one of the most important elements of the model, as it ultimately determines the general RBC level for individual insurers. Unfortunately, documentation is limited, making it difficult to assess the materiality of some of the modeling choices. In addition, the limited documentation available suggests a potential material gap between the calculated C1 factor and its target level for individual insurers, especially smaller ones. Moody's recommends: (1) more detailed documentation of the adjustment factor and the underlying economic justification, in conjunction with the doubling of C1 factors for the top-10 largest issuers; (2) further exploring the data and methods used to estimate the portfolio adjustment factors, to ensure they are effective for corporate as well as non-corporate issuers, (3) design the factors to align incentives with the economic risks, and (4) design a structure that brings together the portfolio adjustment factors along with the doubling of C1 of the 10 largest issuers.

4.2.2 Review and Analysis Performed by Moody's Analytics

The base C1 factors reported in **Table 4** represent the capital required for the representative portfolio described in Section 3.4 for each rating category. As recognized in the C1 Factor Proposal, an individual insurer's portfolio can differ significantly from the representative portfolio in rating composition, number of bonds, and holding amount of each bond. Hence, adjustment to the base C1 factor according to the individual insurer's portfolio characteristics is needed to avoid significant over/under capitalization. There are two proposed adjustments.

First, the C1 factors of the 10 largest issuers held across all debt related asset classes are doubled. The initial filter excludes bonds with C1 RBC equal to 0 and NAIC 1 bonds. As applicable after the first filter, if a top-10 issuer has NAIC 1 bonds, they are added back. Up to 10 bond issuers of a bond portfolio can be subject to the top-10 doubling rule for concentration risk.

Second, the proposed guidelines also include updated base C1 factor adjustment in the form of a scaling factor that is a function of the number of unique issuers in an individual insurer's portfolio (see **Table 5** for details). Regrettably, there is very limited documentation on exactly how these adjustment factors are calculated. To supplement our knowledge, we conducted several interviews with the ACLI and its members. Our best understanding is that the adjustment factors are calibrated roughly according to the following steps:

1. Collect the bond portfolios from 677 actual life insurers.
2. Run the simulation model described in Section 5.2 on these portfolios to determine the capital required to cover 96th percentile statistical safety level for each portfolio.
3. Determine the RBC for each bond in a portfolio using the base C1 factor reported in **Table 4**, multiplied by the scaling factor, which is tiered according to the number of issuers. Solve a set of optimal scaling factors, one for each portfolio size bucket (i.e., unique issuers in the portfolio), so that the scaled portfolio RBC matches the capital required from the simulation in Step 2 as closely as possible across all 677 portfolios.

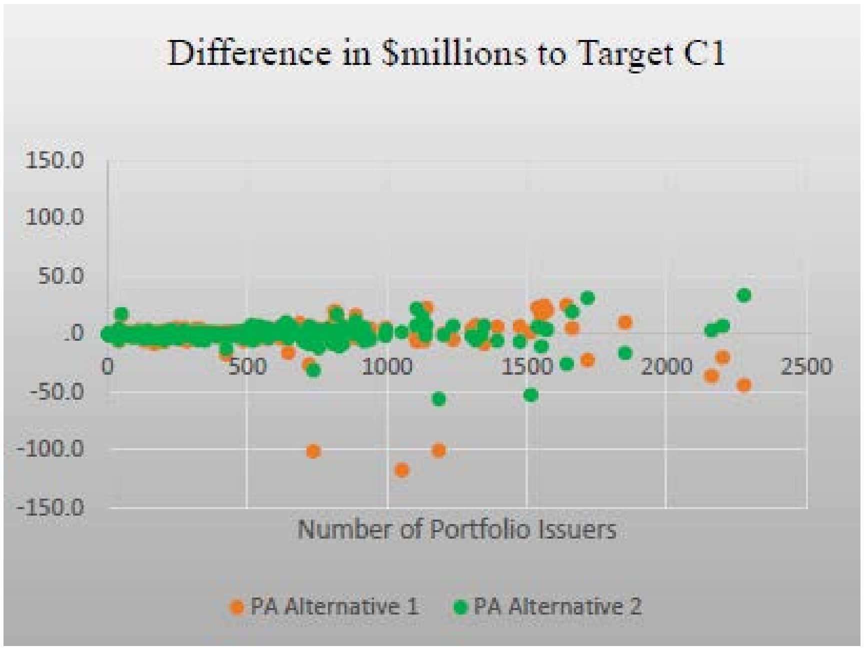
While Moody's Analytics recognizes the importance of these adjustments, we are left questioning the economic justifications of the modeling choices and their materiality:

1. Doubling of capital for the top-10 issuers:
   a. The treatment to double the base C1 factors for top-10 issuers seems arbitrary; why "10", and not, say "20"? why "double", and not, say, "triple". In addition, it is also not clear why this treatment is needed on top of the portfolio adjustment factors.

2. The portfolio adjustment formula:
   a. "Issuer count" is a relatively coarse measure of diversification. While the portfolios used in estimating the relationships between the number of issuers and the cited adjustment factors may have exhibited the cited relationship, there is an incentive to manipulate portfolio composition by holding a small amount in many issuers, which can impact solvency risks. Ideally, the adjustment should align incentives with the economic risks. In this case, concentration is impacted by the total exposure to an issuer, as well as issuer characteristics, including default probability and terms and conditions, including maturity and expected recovery.
   b. The criteria determining the portfolio adjustment factor algorithm are not documented clearly, even though the factors have been updated multiple times: (American Academy of Actuaries, 2016), in June 2017 (American Academy of Actuaries, 2017) and in October 2017 (American Academy of Actuaries, 2017). . The final portfolio RBC using the portfolio adjustment factor may deviate substantially from the actual capital needed for some insurer's portfolio, even though, on average, the gap may be small. We note, that in a presentation deck

prepared by Academy (Bennett & Owens, 2016), analysis is done comparing the C1 factors after the adjustment against the target level for all 677 portfolios based on an early version of the model. **Figure 4** presents analysis results. Due to scaling issues, it is difficult for us to discern from the figure the exact magnitude of the gaps. It appears to be the case though that the gap, on a percentage scale, is larger for smaller sized portfolios, given that the dollar amount of the gap seems relatively flat across different portfolio sizes.

Figure 4: Difference to Portfolio Target C1 Factor



With no access to the underlying portfolios, and limited access to validation and backtesting that examines the appropriateness of doubling capital for the top-10 issuers, or the adjustment factors, especially for smaller portfolios, it is difficult for us to weigh in on the materiality of this issue directly. Rather, we conduct a set of stylized case studies described below.

The stylized case studies assess materiality of issuer diversification on portfolio risk. While the exercise quantifies issuer diversification effects, the simplifying assumptions are broad and provide indicative guidance for additional analysis — worth noting, the exercise abstracts from heterogeneity in notional (holding amount), maturity effects, as well as diversification across industry and asset class discussed elsewhere in this report. If the intent of the portfolio adjustment factors is to capture a more comprehensive set of diversification factors beyond issuer, then this exercise should be redesigned.

Table 17 presents portfolio adjustment formula calibrated to highly stylized Moody's data and based on the standard deviation of losses for hypothetical A2 and Ba1 rated credit portfolios, with the adjustment normalized to the portfolio with 500 issuers. Each portfolio is analyzed separately, and all issuers are homogeneous with equal notional (weight) and with the following characteristics:

- Moody's Idealized Default Probabilities, as specified in **Table 7**
- 0% recovery
- Moody's Analytics GCorr-implied one-step average pairwise default correlations for a sample of Moody's corporate rated issuers, noting that other asset classes can exhibit very different pairwise correlation patterns.[16]
  - A2 One-Year 0.6%
  - A2 Ten-Year 6.2%
  - Ba1 One-Year 3.1%
  - Ba1 Ten-Year 9.9%

We now compare how the factor adjustments relate to the number of issuers. Exploring the doubling the C1 for the 10 largest issuers, we can see the first 10 issuers of the One-Year A1 portfolio exhibits a risk level 3.13 times the level of the normalized 501st

[16] See (Moody's Analytics, 2008) for detailed methodology and validation.

issuer (row labeled "Next 300"). Meanwhile, the One-Year Ba1 portfolio of 10 issuers exhibits a level of risk that is 1.79 times greater.

Moving on to the portfolio adjustment factors, we see that for the aforementioned stylized homogeneous portfolios, most of the diversification is achieved with 200 issuers; increasing the number of issuers from 200 to 500 reduces the A2 One-Year adjustment by 2%, with limited diversification beyond 500.

Given the stylized nature of our exercise, as well as the limited access we had to the model and underlying data, we will not draw hard conclusions from comparing **Table 17** against **Table 5** that would suggest the proposed portfolio adjustment factors do appear to overly penalize insurers with smaller portfolios, a concern that has been echoed by the insurance industry. Rather, we interpret the stylized portfolio results in **Table 17** as providing indicative guidance for needed additional analysis.

Table 17: Portfolio Adjustment Formula Calibrated to Stylized Moody's Data for One- and Ten-Year Horizons

Number of Issuers	A2		Ba1	
	One-Year	Ten-Year	One-Year	Ten-Year
Up to 10	3.13	1.43	1.79	1.30
Next 90	1.17	1.01	1.03	1.00
Next 100	1.02	1.00	1.00	1.00
Next 300	1.00	1.00	1.00	1.00
Over 500	0.99	1.00	1.00	1.00

With these observations in hand, Moody's recommends: (1) more detailed documentation of the portfolio adjustment factors, the underlying economic justification in conjunction with the doubling of C1 factors for the top-10 largest issuers; (2) further exploring the data and methods used to estimate the portfolio adjustment factors, and ensuring they are effective for corporate as well as non-corporate issuers; (3) designing the factors to align incentives with the economic risks; and (4) designing a structure that brings together the portfolio adjustment factors along with the doubling of C1 of the 10 largest issuers.

4.3 Risk Premium

4.3.1 Summary of Moody's Analytics Significant Areas of Review and Recommendations

The current assumption of setting the Risk Premium equal to expected loss appears to be overly conservative. While the C1 Factor Proposal recognizes the inconsistency, it points out that the 1992 guidelines defined the Risk Premium in this way, and in conjunction with other parameters, some of which (e.g., AVR) are beyond the scope of this report. While Moody's appreciates the desire to incorporate conservativeness into assumptions, inputs for which accurate proxies are available should be directly used, and rather incorporate the conservative overlay into the final steps to facilitate model transparency. Moody's recommends a broader evaluation of the various interconnected modeling decisions that lead to setting the Risk Premium at the expected loss level, and aligning the models with a general consensus across the actuarial community, including setting the Risk Premium at a one standard deviation loss.

4.3.2 Review and Analysis Performed by Moody's Analytics

The level of Risk Premium is an important assumption in the calculation of C1 factors. All else equal, the higher the Risk Premium, the lower C1 factors. While the C1 Factor Proposal recognizes the general consensus within the actuarial community that statutory reserves should at least cover moderately adverse loss, which is proxied as a one standard deviation loss (American Academy of Actuaries, 2015), the Risk Premium is set at expected credit loss, calculated as the sum of the product of baseline marginal default rate and average LGD from Years 1–10, with consideration of discounting, tax, and recoverable tax from loss.

While the authors of the C1 Factor Proposal recognize the inconsistency, they point out that the 1992 guidelines defined the Risk Premium in this way and in conjunction with other parameters, some of which (e.g., AVR) are beyond the scope of this report.

Moody's recommends a broader evaluation of the various interconnected modeling decisions that lead to setting the Risk Premium at the expected loss level, and aligning the models with general consensus across the actuarial community, including setting the Risk Premium at a one standard deviation loss. This change should allow for better model transparency and consistency. This issue may be worth considering, along with the pending update to Statutory Accounting Principles that will likely be more aligned with CECL.

5 Key Elements Outside of the Defined Scope

This section reviews the assumptions and methodologies that were out of the Defined Scope. Section 5.1 reviews the applicability of using data based on Moody's rated corporate bonds on all asset classes. Section 5.2 explores the simulation and correlation assumptions. Section 5.3 examines the maturity effect. Section 5.4 reviews the need to more explicitly account for interest income offsets. Section 5.5 discusses the impact of the difference in NRSRO ratings.

5.1 Applicability of Moody's Rated Corporate Data to Other Asset Classes

5.1.1 Summary of Moody's Analytics Significant Areas of Review and Recommendations

C1 RBC base factors were developed using Moody's default rate data on public corporate bond supplemented with S&P's recovery data. After controlling for ratings, we find material differences in observed default, migration, and recovery dynamics across asset classes. These differences question the effectiveness of using Moody's rated public corporate bond data for all asset classes. In the following subsections, we report in more detail our findings related to municipal bonds, structured assets, and private placements.

5.1.2 Municipal Bonds

This section assesses default and recovery dynamics and their comparability to corporate bonds. We first explore differences in default and recovery patterns and later explore data nuances. The authors of the C1 Factor Proposal explained the decision of not developing separate C1 factors for municipal bonds by citing "not able to locate any credible or reliable default or recovery studies (of municipals)". The authors also noted that the rating agencies did not update default studies based on calibrated ratings referencing the recalibration of municipal ratings to the global rating scale by Moody's Investors Service in 2010 (American Academy of Actuaries, 2018). However, there have been material developments in the research of municipal bonds referencing the recalibrated ratings. As a starting point, we cite the observations from a recent study that explores all types of Moody's rated municipal bonds between 1970 and 2019, and bases its findings on re-calibrated historical ratings of municipal bonds to the global rating scale for comparability with corporates (Moody's Investors Service, 2020 (1)). The study finds municipal bonds have: (1) experienced lower default rates, (2) lower rates of rating transitions, and (3) higher recovery rates, than corporate bonds. These observations may not be completely surprising, given municipal and corporate entities are driven by different key rating factors, which are attributed to the different fundamental strengths, weaknesses, and the inherent nature of each sector (Moody's Investors Service, 2010), as demonstrated by their default patterns, which diverge from corporate borrowers, as seen in Table 18.

Delving into the differences:

First, after controlling for rating, historically municipal credits experienced significantly lower cumulative default rates (CDRs), on average, than corporates. These CDRs are calculated by grouping credits by their rating on a particular date into cohorts and then tracking their performance over time, similar to the cohort approach used in the C1 Factor Proposal. Cohorts are formed at monthly frequencies and then averaged over a year. For example, if a credit is rated Aaa on January 1, 2014, it would be grouped into a cohort of other credits rated Aaa on that date, regardless of its original rating (Moody's Investors Service, 2020 (2)). Municipal bonds have lower or equal CDRs than global corporate across all horizons and rating categories, as shown in Table 18. Using the ten-year CDR, relevant when comparing with the C1 RBC factor model, investment-grade global corporate (2.25%) is significantly higher than that of municipal credits (0.1%). For speculative-grade, the CDR of global corporate (28.68%) is about four times the value of municipal credits (7.29%).

Table 18: Cumulative default rates of municipals and corporate rated by Moody's Investors Service

Municipal default rates lower than global corporates for all broad categories
Cumulative default rates, average over the period 1970-2019, municipal vs. global corporate issuers

Municipals

Rating	Average cohort count	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9	Year 10
Aaa	1,003	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Aa	6,980	0.00%	0.00%	0.00%	0.01%	0.01%	0.01%	0.01%	0.02%	0.02%	0.02%
A	4,873	0.00%	0.01%	0.02%	0.02%	0.03%	0.04%	0.06%	0.07%	0.09%	0.10%
Baa	676	0.03%	0.11%	0.21%	0.34%	0.47%	0.61%	0.74%	0.87%	0.99%	1.10%
Ba	111	0.24%	0.67%	1.10%	1.58%	1.98%	2.28%	2.64%	2.99%	3.30%	3.57%
B	23	2.77%	5.48%	8.09%	10.14%	12.20%	13.68%	14.71%	15.46%	16.30%	17.49%
Caa-C	11	8.92%	13.97%	17.22%	19.03%	20.26%	21.51%	22.45%	23.47%	24.45%	25.07%
Investment-grade	13,532	0.00%	0.01%	0.02%	0.03%	0.04%	0.05%	0.06%	0.07%	0.09%	0.10%
Speculative-grade	146	1.29%	2.41%	3.38%	4.20%	4.92%	5.48%	5.98%	6.43%	6.87%	7.29%
All rated	13,678	0.02%	0.03%	0.05%	0.07%	0.08%	0.10%	0.12%	0.13%	0.15%	0.16%

Global Corporates

Rating	Average cohort count	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9	Year 10
Aaa	105	0.00%	0.01%	0.01%	0.03%	0.08%	0.13%	0.18%	0.24%	0.30%	0.36%
Aa	411	0.02%	0.06%	0.11%	0.19%	0.29%	0.40%	0.52%	0.62%	0.71%	0.79%
A	879	0.05%	0.16%	0.33%	0.51%	0.73%	0.98%	1.24%	1.52%	1.81%	2.11%
Baa	847	0.16%	0.41%	0.72%	1.10%	1.47%	1.86%	2.24%	2.65%	3.09%	3.58%
Ba	461	0.88%	2.40%	4.14%	6.01%	7.77%	9.44%	10.93%	12.38%	13.86%	15.40%
B	562	3.26%	7.71%	12.32%	16.52%	20.33%	23.69%	26.68%	29.27%	31.66%	33.70%
Caa-C	337	9.68%	17.19%	23.56%	28.95%	33.56%	37.24%	40.41%	43.32%	45.89%	47.89%
Investment-grade	2,241	0.08%	0.23%	0.42%	0.64%	0.89%	1.14%	1.40%	1.67%	1.96%	2.25%
Speculative-grade	1,360	3.99%	8.06%	11.90%	15.33%	18.34%	20.91%	23.14%	25.13%	26.98%	28.68%
All rated	3,601	1.53%	3.04%	4.43%	5.64%	6.67%	7.54%	8.29%	8.96%	9.59%	10.17%

Second, the rating migration of municipal credits differs remarkably from corporate. Municipal ratings are more stable than corporate ratings over the one-year horizon, 1970–2019, as shown in **Table 19**. For example, on average, 94.63% of Aa rated municipal credit, where most reside, remain in the same rating category over one-year intervals, while only 85.3% of corporate credit does so.

Table 19: Average one-year rating transition rates of municipals and corporate rated by Moody's Investors Service

Municipal ratings transition less frequently than global corporates
Average one-year rating transition rates, 1970-2019, municipal vs. global corporate issuers

From/To:	Average cohort count	Aaa	Aa	A	Baa	Ba	B	Caa-C	Withdrawn	Default
Municipals										
Aaa	1,003	94.81%	1.19%	0.11%	0.03%	0.01%	0.00%	0.00%	3.85%	0.00%
Aa	6,980	0.32%	94.63%	1.03%	0.02%	0.01%	0.00%	0.00%	3.97%	0.00%
A	4,873	0.03%	1.81%	92.73%	0.61%	0.13%	0.01%	0.00%	4.67%	0.00%
Baa	676	0.02%	0.07%	3.39%	89.41%	1.72%	0.21%	0.04%	5.10%	0.03%
Ba	111	0.04%	0.22%	2.10%	4.81%	80.42%	2.74%	0.63%	8.82%	0.23%
B	23	0.00%	0.25%	0.90%	1.02%	5.61%	76.13%	5.35%	8.11%	2.64%
Caa-C	11	0.00%	0.00%	0.69%	0.25%	1.50%	2.73%	72.94%	13.64%	8.25%

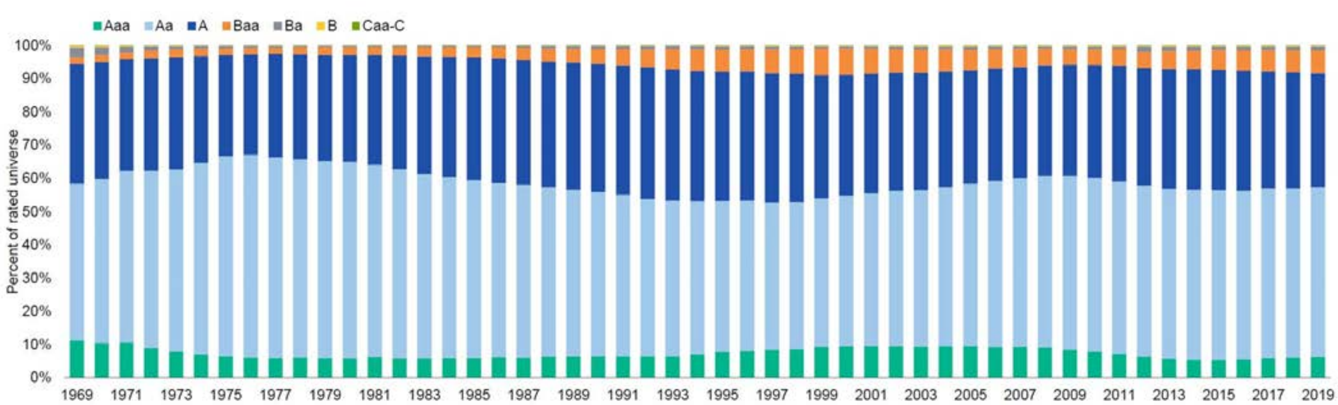
From/To:	Average cohort count	Aaa	Aa	A	Baa	Ba	B	Caa-C	Withdrawn	Default
Global Corporates										
Aaa	105	87.90%	7.78%	0.59%	0.07%	0.02%	0.00%	0.00%	3.63%	0.00%
Aa	411	0.79%	85.30%	8.46%	0.42%	0.06%	0.03%	0.02%	4.90%	0.02%
A	879	0.05%	2.48%	86.99%	5.18%	0.46%	0.10%	0.04%	4.65%	0.05%
Baa	847	0.03%	0.13%	4.02%	86.12%	3.59%	0.65%	0.16%	5.15%	0.16%
Ba	461	0.01%	0.04%	0.40%	6.14%	76.53%	7.00%	0.81%	8.25%	0.84%
B	562	0.01%	0.03%	0.13%	0.44%	4.84%	73.67%	7.05%	10.81%	3.04%
Caa-C	337	0.00%	0.01%	0.02%	0.08%	0.32%	5.94%	69.64%	15.10%	8.89%

Third, Average issuer-weighted recoveries on Moody's-rated municipal bonds since 1970 have been about 68%, significantly higher than the issuer-weighted average 47.7% ultimate recovery rate for senior unsecured bonds of North American corporate issuers since 1987 (Moody's Investors Service, 2020 (2)).

We now discuss nuances with the data (referenced in the Moody's study) that should be recognized if used in estimating distinct municipal C1 factors.

First, municipal credits are concentrated heavily in investment-grade (see **Figure 5**). The average proportion of investment-grade for municipal bonds 1970–2019 is 98.9%, while only 62.2% of corporate bonds are rated investment-grade during the same period. Since there is a limited number of speculative-grade municipal bonds, data from other asset classes may be needed, should a separate model be developed for municipals.

Figure 5: Distribution of Moody's Investors Service Ratings for Municipal Credits (1969–2019)



Source: *(Moody's Investors Service, 2020 (2))*

Second, prior to 2010, municipal bonds were rated using the municipal rating scale, different from the corporate rating scale. Moody's municipal ratings were recalibrated to the global rating scale in May 2010, in order to enhance the comparability of ratings across Moody's rated asset classes. Historical municipal ratings have been adjusted to the global rating scale to ensure comparability of ratings before and after the 2010 rating recalibration exercise. The historical municipal ratings before mid-2010 were first shifted by the average notch of rating shift, by municipal rating scale and sector. If a credit's adjusted rating immediately before the recalibration in mid-2010 differs from its realized recalibrated rating, then the realized recalibrated rating will be extended back to the last rating action date before April 2010. Appendix G of the referenced study (Moody's Investors Service, 2020 (2)) provides a detailed adjustment methodology for historical municipal ratings.

With these observations in mind, Moody's Analytics recommends using municipal default, migration, and recovery data in estimating distinct C1 factors for municipal credit.

5.1.3 Structured Assets

This section assesses the default and recovery dynamics of structured assets and their comparability to corporate bonds. We also evaluate the variations among structured sectors, before and after the Great Recession. As a starting point, we cite the observations from recent studies that explore Moody's rated structured assets between 1993 and 2020 and the underlying data. The studies find marked differences in risk dynamics for structured assets issued on or after January 1, 2009. For the entire study period 1993–2020, structured assets have: (1) experienced higher impairment rates;[17] (2) higher net rating downgrade rates;[18] and (3) lower recovery rates than corporate bonds. For post-2009 issuance,[19] structured assets have (1) close-to-zero impairment rates and (2) high net rating upgrade rates. These observations may not be completely surprising, given that structured assets experienced severe loss during the Great Recession, and regulations and market surveillance have strengthened over the past decade. We note that structured assets and corporate entities are driven by different key rating factors, which are attributed to the different fundamental strengths, weaknesses, and the inherent nature of each sector (Moody's Investors Service, 2020 (3)). Moody's differentiates structured finance ratings from fundamental ratings (i.e., ratings on nonfinancial corporate, financial institution, and public sector entities) on the global long-term scale by adding (sf) to all structured finance ratings. The addition of (sf) to structured finance ratings should eliminate any presumption that such ratings and fundamental ratings at the same letter grade level will behave the same. The (sf) indicator for structured finance security ratings indicates that otherwise similarly rated structured finance and fundamental securities may have different risk characteristics. Through its current methodologies, however, Moody's aspires to achieve broad, expected equivalence in structured finance and fundamental rating performance when measured over a long period of time.

Delving into the differences:

First, structured assets have remarkably higher impairment rates than the global corporate, based on historical experiences 1993–2020 (see Table 20). For U.S. RMBS/CMBS/ABS, the impairment rates are at least multiple times higher than the corporate default rate, with U.S. RMBS on average comprising more than half of structured tranches 1993–2020h1. Only Global CLOs have lower impairment rates than corporate.

[17] Due to the unique nature of structured assets, impairment is commonly used to describe the financial loss events. A security is impaired when investors receive — or expect to receive with near certainty — less value than would be expected if the obligor were not experiencing financial distress or otherwise prevented from making payments by a third party, even if the indenture or contractual agreement does not provide the investor with a natural remedy for such events, such as the right to press for bankruptcy (Moody's Investors Service, 2020 (1)).There are two types of impairments — principal impairments and interest impairments. Securities with principal impairments are those that had outstanding principal write-downs or losses greater than 50 basis points (bps) of the tranche original balance or securities currently carrying Ca or C ratings, even if they have not yet experienced an interest shortfall or principal write-down. Securities with interest impairments, or interest-impaired securities, are those that are not principal impaired but have outstanding interest shortfalls greater than 50 bps of the tranche original balance. Because interest shortfalls are cured at fairly high frequency within a short period, we record an interest impairment only if the 50 bps shortfall has been outstanding for 12 months or longer (Moody's Investors Service, 2020 (1)). The vast majority of impairments are principal impairments.

[18] Net rating downgrade rate refers to the difference between 12-month average rating downgrade rate and upgrade rate.

[19] Post-2009 issuance refers to structured asset securities issued on or after January 1, 2009.

Table 20: Average one-year default/impairment rate of securities rated by Moody's Investors Service[20]

Average one-year default/impairment rate

Rating	Global Corporate*	US RMBS**	US CMBS**	US ABS**	Global CLO**	All Structured Finance***
Aaa	0.00%	0.59%	0.02%	0.03%	0.00%	0.46%
Aa	0.02%	4.74%	0.08%	0.20%	0.00%	2.76%
A	0.05%	5.49%	0.27%	0.17%	0.01%	3.00%
Baa	0.16%	9.31%	0.84%	0.50%	0.06%	5.70%
Ba	0.84%	12.37%	3.66%	2.30%	0.14%	7.88%
B	3.04%	14.96%	7.77%	5.91%	0.50%	11.95%
Caa-C	8.89%	20.40%	23.92%	16.43%	2.45%	19.81%

*global corporate default rate 1970-2019

**structured asset impairment rate by sector 1993-2020h1

**impairment rate for all structured assets 1993-2020h1

Source: Moody's Investors Service

In contrast, for post-2009 issuance, impairments become rare. The average one-year impairment is only 0.04% 2009–2019. U.S. RMBS, U.S. ABS, and Global CLOs even have zero impairment (see **Table 21**). There have been notable changes that may contribute to this strong performance (S&P Global, 2019).

» Regulation

- Increased disclosure requirements, for instance, the simple, transparent, and standardized (STS) designation.
- New risk retention rules for certain sectors, such as the 5% risk retention requirement for originators, and increased regulatory capital charges for some investors.
- Limits to the origination of certain products, such as self-certified mortgages in the U.K., and increased focus on loan affordability, such as the ability-to-repay (ATR)/qualified mortgage (QM) rule in the U.S.

» Market structure

- Shift toward nonbank sponsors and emergence of private portfolio lenders.
- Less use of leverage by investors and more "buy and hold" investments.
- Decreased rated issuance compared to pre-crisis levels.

» Securitization structures

- More sequential pay structures which, all else equal, provide more protection to senior bondholders.
- Generally, more seasoned and less leveraged structures.
- Certain structures, such as subprime RMBS and CDOs of ABS,[21] have broadly disappeared.

[20] The default/impairment rates are the fractions of default/impairment from the empirical one-year rating transition matrices for global corporate and structured asset classes provided by Moody's Investors Service.

[21] CDOs of ABS are securities backed by a collateral pool made of other structured tranches. This is different from conventional ABS, such as ABS backed by student loans.

Table 21: 12-month impairment rate for structured tranches issued on or after January 1, 2009 and rated by Moody's Investors Service 2009-2019

12-month impairment rate and cohort size for Global SF by sector

	Impairment rate			Count		
Sector	This year*	5-year avg.**	Hist. avg.***	This year*	5-year avg.**	Hist. avg.***
US ABS	0.00%	0.00%	0.00%	2,332	2,209	1,566
US RMBS	0.00%	0.00%	0.00%	2,876	1,337	586
US CMBS	0.00%	0.12%	0.09%	2,946	2,505	1,477
Global CDOs ex CLOs	0.00%	0.00%	0.00%	282	293	193
Global CLOs	0.00%	0.00%	0.00%	5,834	3,735	1,696
EMEA SF ex CDO & Other	0.00%	0.03%	0.02%	1,611	1,378	1,069
Intl SF ex CDO & Other	0.00%	0.17%	0.20%	1,272	1,012	739
Other SF	0.00%	0.00%	0.00%	2	2	2
Global SF	**0.00%**	**0.04%**	**0.04%**	**17,155**	**12,470**	**7,213**

* This year covers the 12-month period from 1 January 2019 to 31 December 2019.
** 5-yr avg covers the 60-month period from 1 January 2015 to 31 December 2019.
*** Hist. avg. covers the period 1 January 2009 to 31 December 2019.
Source: Moody's Investors Service

Second, the rating transition rates differ between structured assets and corporate, as well as among structured sectors. Given the relatively large number of structured sectors, **Table 22** presents and summarizes the 12-month downgrade and upgrade rates for all structured securities issued in 1993–2020. **Table 23** shows structured securities issued since 2009. We include Global Corporate's Corporate statistics 1984–2020 for comparison.[22] As seen in **Table 22**, Global Structured Finance, overall, have a higher downgrade rate and a lower upgrade rate than Global Corporate (Hist avg. column). This appears to be driven by the performance of U.S. RMBS and Global CDOs. Excluding both sectors, Global Structured Finance has net downgrade rates of approximately 1.02%[23] lower than Global Corporate (4.2%). Understandably, U.S. RMBS and Global CDOs were the most severely impacted sectors during the Great Recession.

In contrast, for structured securities issued since 2009 (see **Table 23**), Global Structured Finance has significantly lower downgrade rates (2.09%) 2009–2020 than Global Corporate (13.63%), while upgrade rates of both sectors are not very different. Remarkably, more Global Structured Finance ratings are upgraded than downgraded. On average, Global Structured Finance ratings have a net upgrade rate of 6.3%, while Global Corporate has a net downgrade rate of 4.2%.

[22] The period for the corporate average differs, as Moody's Investors Service compares with a long-term, corporate benchmark.
[23] Net downgrade rate is the difference between downgrade rate and upgrade rate.

Table 22: Global structured finance 12-month downgrade and upgrade rates by sector (structured asset securities issued in 1993–2020)

	12-month downgrade rate				12-month upgrade rate			
	2020H1*	2019H1*	5-yr avg.**	Hist avg.***	2020H1	2019H1	5-yr avg.	Hist avg.
US ABS, CMBS, & RMBS	4.93%	2.25%	3.52%	17.10%	9.57%	12.84%	15.87%	5.31%
US ABS	3.02%	1.73%	3.90%	5.80%	8.72%	10.69%	11.88%	4.84%
US Auto Loans	0.00%	0.00%	0.10%	1.86%	18.09%	24.22%	22.10%	12.13%
US Credit Cards	0.00%	0.00%	0.65%	1.68%	7.10%	4.22%	2.98%	2.96%
US Student Loans	3.57%	2.19%	6.67%	5.59%	3.65%	4.54%	9.82%	2.41%
US Equipment Lease	0.00%	0.00%	0.00%	2.83%	24.76%	18.32%	19.72%	8.70%
US RMBS	5.85%	2.27%	3.35%	20.49%	12.26%	15.28%	18.92%	4.71%
US CMBS	4.18%	2.70%	3.77%	12.53%	2.61%	5.28%	8.76%	8.85%
excl CRE CDOs	4.44%	2.88%	4.02%	10.87%	2.72%	5.34%	8.39%	9.01%
EMEA ABS, CMBS, & RMBS	2.85%	6.90%	3.92%	8.98%	9.77%	12.98%	16.75%	7.95%
Asia-Pacific ABS, CMBS, & RMBS	0.51%	0.00%	0.20%	5.07%	8.82%	11.13%	8.25%	4.16%
Latin America ABS, CMBS, & RMBS	32.20%	0.00%	11.26%	12.04%	5.65%	2.12%	7.42%	7.81%
Global CDOs ex CLOs	0.00%	0.92%	0.87%	22.32%	14.43%	15.18%	16.40%	7.53%
Global CLOs	1.72%	0.54%	0.93%	7.44%	2.25%	3.08%	5.31%	14.72%
US CLOs	1.77%	0.73%	0.98%	7.17%	2.15%	3.24%	4.29%	14.44%
EMEA CLOs	1.62%	0.00%	0.80%	8.25%	2.48%	2.64%	8.10%	15.57%
Global structured finance	3.84%	2.23%	2.96%	15.72%	7.92%	11.03%	13.78%	6.27%
excl US RMBS and SF CDOs	2.75%	2.17%	2.66%	9.23%	5.58%	7.69%	9.93%	8.21%
Global corporate	16.37%	8.09%	11.82%	13.63%	4.86%	9.37%	9.14%	9.43%

* 2020H1 covers the 12-month period from July 1, 2019 to June 30, 2020; 2019H1 covers the 12-month period from July 1, 2018 to June 30, 2019

** 5-yr avg. covers the 60-month period from July 1, 2015 to June 30, 2020

*** Structured finance hist avg. are rates averaged over time period January 1, 1993 - June 30, 2020; corporate hist avg. are calculated over January 1, 1984 - June 30, 2020

Source: Moody's Investors Service

Table 23: Global structured finance 12-month downgrade and upgrade rates by sector (structured asset securities issued on or after January 1, 2009)

Global structured finance 12-month downgrade and upgrade rates by sector

	12-month downgrade rate				12-month upgrade rate			
	2020H1*	2019H1*	5-yr avg.**	Hist avg.***	2020H1	2019H1	5-yr avg.	Hist avg.
US ABS, CMBS, & RMBS	1.89%	0.75%	1.12%	1.13%	12.08%	11.75%	11.69%	11.08%
US ABS	1.92%	0.35%	0.97%	0.72%	10.70%	12.62%	13.99%	13.76%
US Auto Loans	0.00%	0.00%	0.10%	0.05%	18.09%	24.22%	22.10%	23.15%
US Credit Cards	0.00%	0.00%	0.75%	0.66%	7.43%	4.58%	3.44%	6.36%
US Student Loans	1.09%	0.32%	1.48%	1.00%	4.05%	4.06%	12.63%	8.02%
US Equipment Lease	0.00%	0.00%	0.00%	0.00%	24.76%	18.32%	19.72%	20.31%
US RMBS	0.00%	0.00%	0.00%	0.00%	22.43%	21.51%	21.18%	20.87%
US CMBS	3.95%	1.71%	2.04%	2.14%	1.84%	2.75%	3.17%	3.31%
excl CRE CDOs	4.16%	1.79%	2.18%	1.77%	1.87%	2.71%	2.76%	3.05%
EMEA ABS, CMBS, & RMBS	3.54%	6.08%	4.51%	7.27%	11.32%	13.92%	13.47%	11.43%
Asia-Pacific ABS, CMBS, & RMBS	0.60%	0.00%	0.22%	1.04%	9.49%	11.89%	9.14%	6.78%
Latin America ABS, CMBS, & RMBS	35.77%	0.00%	10.19%	12.52%	5.11%	2.82%	8.45%	11.19%
Global CDOs ex CLOs	0.00%	0.00%	0.20%	2.10%	5.76%	2.70%	4.81%	6.05%
Global CLOs	1.73%	0.55%	0.84%	0.78%	2.23%	2.76%	2.11%	2.10%
US CLOs	1.77%	0.74%	0.88%	0.80%	2.14%	2.92%	2.17%	2.16%
EMEA CLOs	1.63%	0.00%	0.71%	0.72%	2.44%	2.28%	1.92%	1.90%
Global structured finance	2.12%	1.13%	1.39%	2.09%	8.28%	8.74%	8.49%	8.39%
Global corporate	16.37%	8.09%	11.82%	13.63%	4.86%	9.37%	9.14%	9.43%

* 2020H1 covers the 12-month period from July 1, 2019 to June 30, 2020; 2019H1 covers the 12-month period from July 1, 2018 to June 30, 2019

** 5-yr avg. covers the 60-month period from July 1, 2015 to June 30, 2020

*** Structured finance hist avg. are rates averaged over time period January 1, 2009 - June 30, 2020; corporate hist avg. are calculated over January 1, 1984 - June 30, 2020

Source: Moody's Investors Service

Finally, the recovery rates of structured assets are notably different from corporate bonds. Given the scarcity of recovery data for the post-2009 issuance, we present recovery statistics 1993–2019. Moody's Investors Service examined LGDs for the 24,714 global impairments, for which final resolved loss data is available.

During 1993–2019, the average LGD rate for all resolved principal impaired securities was 84% of the original balance. As seen in **Table 24**, realized final LGD rates by sector for resolved principal impairments 1993–2019. U.S. RMBS accounts for the vast majority of impairments among all structured asset classes, with U.S. CMBS a distant second. For investment-grade tranches by rating at issuance, U.S. RMBS and CMBS have significantly higher LGDs than U.S. ABS and Global CLOs, with Global CDOs having the highest LGD. For speculative-grade tranches, U.S. ABS and Global CLOs still have lower LGDs than U.S. CMBS.

In comparison, the issuer-weighted average ultimate recovery rate is 47.7% for North American senior unsecured corporate bonds issued since 1987, implying LGD of 52.3% (Moody's Investors Service, 2020 (2)). U.S. RMBS/CMBS/ABS (both investment-grade and speculative-grade) all have higher LGDs than corporate. The investment-grade Global CLOs have lower LGD than corporate, while the speculative-grade CLOs have higher LGD than corporate.

Table 24: Realized final LGD rates by sector for resolved principal impairments 1993–2019

Realized final LGD rates by sector for resolved principal impairments by asset class, 1993-2019

	Investment-grade at issuance (% Original balance)		Speculative-grade at issuance (% Original balance)	
Asset class	Counts	Mean	Counts	Mean
US ABS	**190**	**59.6%**	**40**	**73.5%**
Small Business Loans	69	81.5%	na	na
Franchise Loans	40	74.4%	17	96.0%
Student Loans	25	12.6%	-	0.0%
Equipment Leases	41	38.2%	15	47.8%
US RMBS/HEL/MH	**18,447**	**83.3%**	**2,258**	**81.5%**
Alt-A/Option ARM	8,617	82.1%	551	80.7%
Jumbo	1,001	39.0%	227	44.4%
HELOC	51	99.6%	20	89.7%
Scratch & Dent	330	90.9%	64	72.7%
Subprime Firsts	7,111	89.2%	1,029	88.2%
Subprime Seconds	983	96.0%	192	94.0%
Manufactured Housing	120	90.0%	35	95.4%
US CMBS	**769**	**90.6%**	**1,291**	**92.2%**
Conduit/Fusion	611	94.5%	1,187	93.4%
CRE CDO	67	88.5%	29	73.1%
Small Balance Commercial	36	81.0%	49	93.2%
Large Loan	51	60.1%	23	54.5%
EMEA ABS,CMBS,RMBS	**42**	**54.9%**	**29**	**40.0%**
INTL ABS,CMBS,RMBS	**52**	**75.2%**	**56**	**95.7%**
Global CLOs	**15**	**34.0%**	**11**	**85.6%**
Global CDOs	**1,416**	**91.6%**	**98**	**96.6%**
HY CBOs				
SF CDOs	1,373	91.8%	87	96.9%
Syn Arbitrage	29	92.8%	na	na

Assets with counts less than 10 are not shown.
Source: Moody's Investors Service

While Moody's Analytics recognizes the data challenges and model complexities of modeling the various structured asset classes across historic periods, the observations above are sufficiently stark enough that we recommend assessing the use of structured data on default/impairment, migration, and recovery when estimating distinct C1 factors for structured assets.

5.1.4 Private Placement Credits

This section assesses default and recovery dynamics of private placement credits and their comparability with Moody's rated corporate bonds. Private placements refer to instruments, issued in reliance on a statutory or rule-based exemption from the registration requirements imposed by the Securities Act of 1933. Broker-dealers that recommend or sell private placements have additional requirements under FINRA and SEC rules, which include filing certain offering documents and ensuring the suitability of any recommended investments (FINRA, 2021). Private placements are usually unrated by NRSRO but can have equivalent credit designations from NAIC.

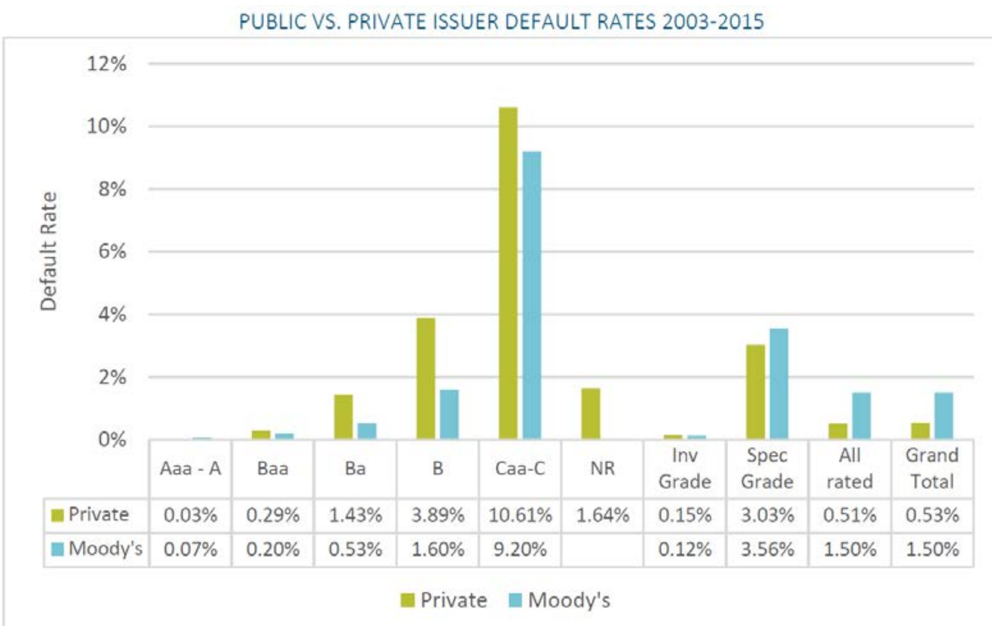
As a starting point, we cite the observations from a recent study that explores the default and recovery experiences of private placement credits in 2003–2015 (Society of Actuaries, 2019). The study is based on data contributed by 20 insurers over the 2003–2015 period that covers 14,142 CUSIPs. The study finds that, when compared with comparable Moody's rated corporates:

- Investment-grade private placement credits have experienced similar default rates
- Speculative-grade private placement credits have experienced higher default rates
- Placement credits have different rates of rating transitions
- Placement credits have higher recovery rates

Delving into the differences:

First, investment-grade default rates are low for both private placements issuers (0.15%) and public corporates (0.12%), respectively (see **Figure 6**, the investment-grade column). [24] Private issuers have higher default rates for all ratings Baa and lower. Since the private placement data from the participating companies are heavily skewed towards investment-grade, the overall default rate for rated bonds is lower for private issuers (0.51%) than Moody's rated issuers (1.50%). The quality mix difference also explains why private issuers have lower, overall speculative-grade default rates. The ratings of speculative-grade private issuers are more concentrated in Ba, while Moody's rated corporates are more concentrated in B and below.

Figure 6: Average one-year issuer default rates of public versus private issuer[25]



Source for public bonds: (Moody's Investors Service, 2018)
Source for private bonds: (Society of Actuaries, 2019)

Second, the rating transition patterns differ between private placements and Moody's rated corporates. As seen in **Table 25**, constructed using the internal ratings of investors, private placements have a significantly higher probability of Withdrawn Rating

[24] The default rates of private placement issuers are measured by incident rate of Credit Risk Events (CRE). CRE is parallel to default referenced by rating agencies except for two other types of events:

- the sale of a private placement bond at a price less than or equal to 70 cents on the dollar
- any other credit event that a contributor substantiated as a default-like credit deterioration but, due to the nuances of the private placement market, does not fit the definitions above.[15] The purpose of including these types of events as CREs is to avoid understatement of the incidence of CREs for situations that, in similar circumstances with public bonds, would have most likely resulted in a default.

[25] The chart was constructed by the Society of Actuaries, with reference to data from Moody's Investors Service.

(WR)[26] than Moody's rated corporates (see **Table 26**) especially for Aaa and speculative grades. With the exception of Aaa, private placements have similar or lower rating transition rates than Moody's rated corporates for investment-grade. For speculative grades, especially B and below, private placements have a higher rate of rating transition than Moody's rated corporates.

Table 25: One-year rating transition rate of private placement credits (2003–2015)

MOST RECENT INTERNAL RATINGS ONE-YEAR MIGRATION RATES

From	To AAA	AA	A	BBB	BB	B	CCC	<CCC	CRE	WR
AAA	**83.65%**	4.57%	1.10%	1.53%	0.05%	0.03%	0.00%	0.00%	0.00%	9.06%
AA	0.73%	**88.75%**	5.29%	0.55%	0.07%	0.01%	0.01%	0.01%	0.01%	4.56%
A	0.03%	1.03%	**87.77%**	5.86%	0.12%	0.03%	0.04%	0.00%	0.03%	5.10%
BBB	0.02%	0.03%	1.68%	**88.97%**	2.05%	0.25%	0.02%	0.03%	0.22%	6.74%
BB	0.03%	0.03%	0.41%	6.50%	**75.23%**	3.15%	0.79%	0.36%	1.63%	11.86%
B	0.00%	0.00%	0.15%	0.80%	6.15%	**66.48%**	2.84%	1.89%	5.13%	16.56%
CCC	0.00%	0.00%	0.00%	0.60%	1.20%	6.08%	**56.97%**	5.98%	10.56%	18.63%
<CCC	0.00%	0.00%	0.00%	0.94%	1.31%	4.50%	0.94%	**65.29%**	7.32%	19.70%

Source: (Society of Actuaries, 2019)

Table 26: One-year rating transition rate of public corporates rated by Moody's Investors Service (1970–2019)

From/To:	Average cohort count	Aaa	Aa	A	Baa	Ba	B	Caa-C	Withdrawn	Default
Global Corporates										
Aaa	105	87.90%	7.78%	0.59%	0.07%	0.02%	0.00%	0.00%	3.63%	0.00%
Aa	411	0.79%	85.30%	8.46%	0.42%	0.06%	0.03%	0.02%	4.90%	0.02%
A	879	0.05%	2.48%	86.99%	5.18%	0.46%	0.10%	0.04%	4.65%	0.05%
Baa	847	0.03%	0.13%	4.02%	86.12%	3.59%	0.65%	0.16%	5.15%	0.16%
Ba	461	0.01%	0.04%	0.40%	6.14%	76.53%	7.00%	0.81%	8.25%	0.84%
B	562	0.01%	0.03%	0.13%	0.44%	4.84%	73.67%	7.05%	10.81%	3.04%
Caa-C	337	0.00%	0.01%	0.02%	0.08%	0.32%	5.94%	69.64%	15.10%	8.89%

Third, the recovery rate of senior unsecured private placements 2003–2015 (62.2%) is higher than the issuer-weighted, average 47.7% ultimate recovery rate for senior unsecured bonds of North American corporate issuers since 1987 (Moody's Investors Service, 2020 (2)). It is recognized that private placement credits have customized covenant protections to investors (Society of Actuaries, 2019). This could contribute to higher recovery rates for private placement credits than public corporate.

It is noted that the private placements data may be subject to challenges, such as change in asset IDs and miscoded ratings. While the Private Placement Experience Committee at the Society of Actuaries has reviewed and detected the data issues, some errors may remain and affect the rating transition matrices. In addition, the experience data was provided by 20 insurers and may not fully reflect the whole universe.

Since private placement credits have higher default rates for Baa and below ratings and higher recovery rate than what is observed for Moody's rated corporates, additional data and analysis may be needed to assess whether C1 factors will be larger or smaller than currently proposed if private placement credits data is used for C1 factors development. While recognizing the data challenges and scarcity of references, Moody's recommends exploring a centralized collection of default, migration, and recovery data that can later be used in further estimating distinct C1 factors and for other purposes.

[26] Withdrawn Rating (WR) includes the events where assets have matured, been sold, or called. This classification also includes a very small proportion of assets that migrated from a letter rating to no rating submitted by the participating companies in the following year.

5.2 Simulation and Correlation

5.2.1 Summary of Moody's Analytics Significant Areas of Review and Recommendations

The current C1 factor model does not account for variation in cross-industry and cross-asset class concentration risks nor diversification that may be different across life companies' portfolios. These variations can be material, and we recommend additional analysis that assesses the materiality of abstracting from cross-industry and cross-asset class differentiation.

5.2.2 Review and Analysis Performed by Moody's Analytics

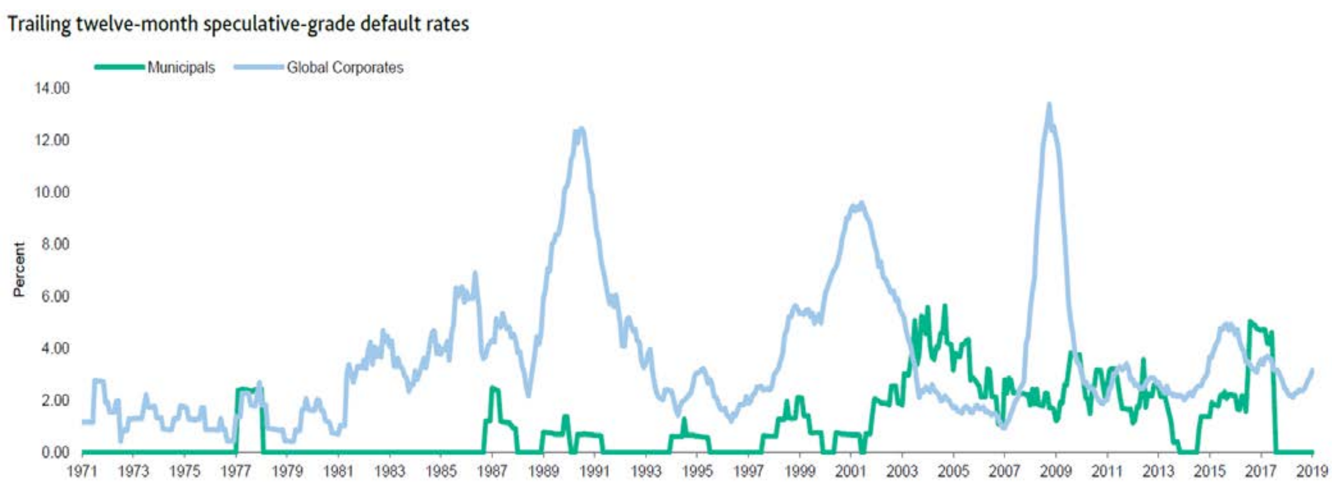
The representative portfolio is simulated for each alphanumeric rating when computing C1 factors. For example, the C1 RBC factor for Aaa rated bonds is computed independently of the C1 factor for A or Baa ratings. The simulated economic state determines the leveled economic scalar that adjusts baseline default rates for each counterparty. If a bond defaults in any year *t* before Year 10, then the full principal is assumed to be reinvested with the same initial rating and maturity (10-*t*) years. For example, if an Aa1 bond defaults at Year 3, then the full principal is assumed to be reinvested in an Aa1 bond with 7 years maturity. The cashflows are discounted to present value by 5% pre-tax/3.25% after-tax per annum, approximately the average 10-year LIBOR swap rates 1994–2013. The tax rate for assets carried at market value is assumed to be 35%. 80% of tax is assumed to be recoverable when default occurs.

The approach of separately simulating each rating makes sense in the context of stylized sub-portfolios that exhibit no diversification benefits when combined. This is generally not the case with credit portfolios, which often have a range of industry, country, and asset-class (e.g., Muni, corporate) exposures. In addition, setting the representative portfolio as having the same level of counterparty concentration and its impact on portfolio risk is worth exploring further.

To better understand the materiality of cross-asset class diversification benefits, we explore their historical default rates and the extent to which they are correlated.

Figure 7 demonstrates historical default rates of speculative-grade municipal bonds and global corporates are not strongly correlated — if they were, the two series would move in lockstep. For example, during the 2001 dot-com bubble, when the speculative-grade corporate default rate skyrocketed, default of similar-rated municipal bonds remained rare. This follows, as municipal and corporate bonds are driven by different underlying risk factors.

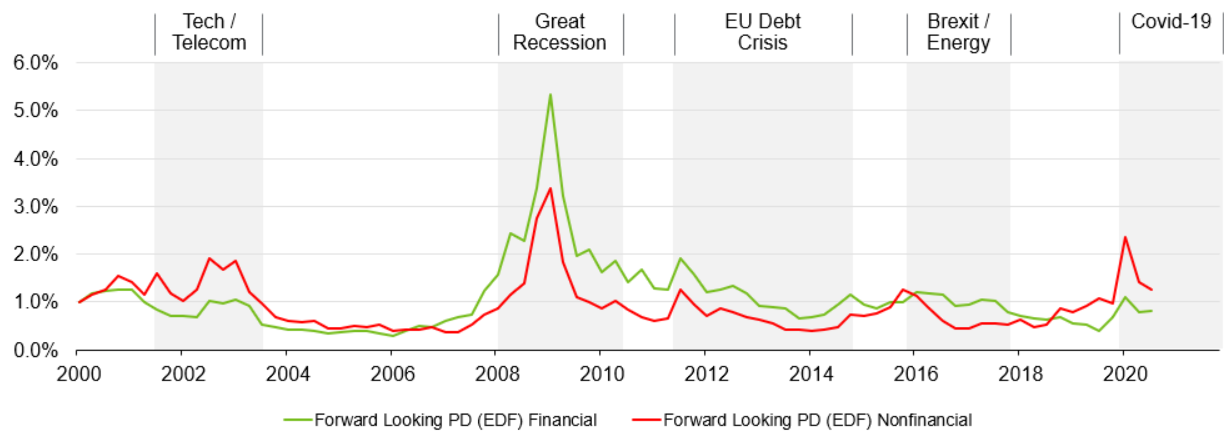
Figure 7: Historical default rate of speculative-grade municipal bonds and global corporates



Source: Moody's Investors Service

In a similar vein, **Figure 8** presents the average annualized default probability, using the Moody's Analytics EDF™ (Expected Default Frequency) credit measure, across all U.S. Financial and Non-financial publicly listed firms. We can see the Tech and Telecom companies deteriorated in credit quality during the early 2000s, with financial institutions weathering reasonably well. Financials' default probabilities increased in a more pronounced manner at the onslaught of the Great Recession, and they have weathered the current COVID-19 crisis reasonably well.

Figure 8: Average One-Year Default Probabilities for Financials and Non-Financial Firms in the United States (normalized so that 2000 probabilities = 1%)



Source: Moody's Analytics

The desire to model these correlations is recognized in (American Academy of Actuaries, 2015); the methodology and data did not lend to segmentation:

> While credit recognized as we considered the use of default rates that varied by industry sector, however, there was limited data available. In addition, there are practical considerations with how to classify bonds by industry. Hypothetically, if sufficient data were available, a model with industry correlation factors could be built. As such data is not available, we assume correlations are implicit in the default data.

We recognize the challenges of using default data for rated corporate borrowers — in particular, the dearth of data limits segmentation. There, however, is a wide range of data and modeling approaches that have been developed to overcome this challenge. Moody's Analytics GCorr™ global correlation model, for example, contains over 1,000 credit factors, with coverage including corporate credit (61 industries across over 100 countries) also relevant for CLOs, retail credit in the U.S. (with 6 retail asset types across 51 states/district) that is relevant for ABS and RMBS, over 100 sovereigns, and commercial real estate (with 5 property types across 73 MSAs) relevant for CMBS. When used in conjunction with Moody's Analytics rating transition model we can obtain a granular representation of portfolio risk that accounts for correlated deterioration in credit and default.[27] When used in assessing diversification, we find corporate industry credit factors within each country are, on average, in the order of 85% correlated, but can exhibit correlations as low as 70%. Meanwhile, cross-asset class diversification can be material, with retail, corporate, and commercial real estate factors often having correlations below 50%. While the impact on portfolio risk measures can be substantial, with reductions of in excess of 30%, when imperfect correlations are accounted for, Moody's recognizes the impact is portfolio-specific and dependent upon the specific nature of the risk measures of interest (e.g., greatest default loss, standard deviation).

We further highlight the unique correlation behavior of structured assets, recognizing the underlying collateral often contains a large diversified pool of issuers. The diversified idiosyncratic risk often results in observed, higher level of correlations for structured assets when compared to, say, corporate credit of similar rating (Yahalom, Levy, & Kaplin, 2010).

Thus, our recommendation for additional analysis to assess the materiality of abstracting from cross-industry and cross-asset class differentiation.

5.3 Maturity Effect on Capital Factors

5.3.1 Summary of Moody's Analytics Significant Areas of Review and Recommendations

The C1 factors do not differentiate risk across maturity. This can create a material distorted incentive to hold longer-dated bonds whose credit risk is more sensitive to the credit environment. Moody's recommends exploring a maturity adjustment to the C1 factors.

[27] For details, see (Moody's Analytics, 2012), (Moody's Analytics, 2020), and references therein.

5.3.2 Review and Analysis Performed by Moody's Analytics

RBC factors are calculated for a ten-year horizon and implicitly assume a maturity of 10 years for all bonds (American Academy of Actuaries, 2015). While the assumption provides simplicity, and the 10-year maturity is recognized as in-line with a modified duration of life insurance portfolios, the sensitivity of risk to maturity is material and can distort the desired composition of asset holdings. There are two aspects to this point:

- Lifetime loss — All else equal, including counterparty and recovery, the lifetime loss of a 10-year bond is greater than that of, a seven-year or a one-year bond. A flat default probability term-structure would have lifetime loss increasing linearly with time to maturity; the 10-year bond faces roughly 10 times the expected lifetime loss as the one-year bond.
- Correlated losses — all else equal, including the expected default probability to maturity, default correlation across two counterparties will be lower if the maturity of one is shorter than the other. Events will impact the longer-dated bond after the maturity of the shorter-dated bond. To further intuit this dynamic, consider the extreme case of a consol bond with no maturity date and a one-year bond to the same counterparty. The events that lead to a default on the consol bond are likely to materialize well after the one-year bond matures.

With these observations, it is clear the proposed RBC factors should consider instrument-level maturity. It is worth exploring the assumptions along with the dynamics that are desired to be captured by the model. If the model is intended to measure capital over a 10-year horizon that includes future investments, assuming matured assets are rolled over, there is some (flawed) justification for treating all bonds as having a 10-year maturity. If, say, the one-year bond is rolled over for 10 years with the same counterparty, its lifetime loss will equate to that of the 10-year bond. Let's explore the two sources of maturity effects listed above:

- Lifetime loss — In general, insurance companies invest in high-quality credit, generally facing upward sloping default probability term structures; the 10-year default probability can often be many multiples larger than the 1-year default probability. After all, high credit quality names can only deteriorate in credit over time. Thus, the lifetime loss of the 10-year bond will be substantially higher than the lifetime loss of a strategy involving one-year bonds rolled over into high credit quality counterparties. **Table 7** presents investment-grade Moody's idealized cumulative expected default rates.[28] For AAA, the one-year spot default rate is 0.0001%, while the 10-year spot rate is 0.0018% ((0.0100%-0.0082%)/(1-0.0082%)), almost 20 times larger.
- Correlated losses — The issue outlined above continues to prevail. Default correlations will be lower across two counterparties if the maturity of one bond is shorter than that of the other.

With these observations in mind, we suggest exploring a maturity adjustment similar in spirit to the one found in regulatory capital guidelines for banks put forth by the Bank of International Settlements and described in (Basel Committee on Banking Supervision, 2005).

5.4 Investment Income Offsets

5.4.1 Summary of Moody's Analytics Significant Areas of Review and Recommendations

While investment income can be used to offset loss and support statutory surplus, the C1 factors are modeled with the implicit assumption that all investment profits are fully distributed to policyholders or used to absorb product or operational losses. This introduces a potential bias in differentiating investment income across assets, across rating categories, and across asset classes. Accounting for such heterogeneity in investment income can potentially lead to substantial differences in RBC factors across ratings and asset classes. Moody's recommends more accurately differentiating investment income across assets in the C1 factors.

5.4.2 Review and Analysis Performed by Moody's Analytics

C1 factors are intended to capture the minimum capital amount that protects statutory surplus from the fluctuations that reduce statutory surplus. While investment income can be used to offset loss and support statutory surplus, it is not explicitly modeled in the current framework under the implicit assumption that all investment profits are fully distributed to policyholders or used to absorb product or operational losses.[29]

[28] For a detailed discussion of Idealized Default Rates and their use, see (Moody's Investors Service, 2020 (1)).

[29] There are two exceptions: the investment income generated by the Risk Premium portion of the fund (assumed to be 5%) and the risk-free income on capital included in the model.

This introduces a potential bias in differentiating investment income across assets, across rating categories, and across asset classes. Accounting for such heterogeneity in investment income can potentially lead to substantial differences in RBC factor across ratings and asset classes.

Per the (American Academy of Actuaries, 2015), the current C1 factors were last analyzed in 2002. While the methodology was changed, no changes were made to the original C1 factors first reported in 1994 as a result of this 2002 analysis. Since 1994, there has been a wide range of developments in the credit securities markets, and the sorts of credit that insurance companies are exposed to. Specifically, with the prevalence of increasingly complex credit securities, the relevance and variation in interest income have increased. In some cases, interest income plays a material role in the risk profile of a credit security that is not well approximated through the Risk Premium method. For example, according to (Wells Fargo Securities, 2020), structured instruments offer higher interest income compared to corporate bonds of the same rating. As of October 2020, the average investment-grade corporate bond OAS was 122bps, while the average CLO OAS for different investment-grade ratings ranged from 138-415bps, and the average non-agency CMBS OAS for different investment-grade ratings ranged from 103-892bps.

Moody's recommends more accurately differentiating investment income across assets in the C1 factors.

5.5 Comparability Across NRSROs Ratings

5.5.1 Summary of Moody's Analytics Significant Areas of Review and Recommendations

The model is developed based on Moody's ratings only. However, NAIC rating designations are typically determined by a set of NRSROs ratings. NRSROs have unique differences in credit rating methodologies and do not provide correspondence because they base their credit ratings on a range of qualitative, as well as quantitative, factors. This creates a challenge when mapping ratings across NRSROs to the various NAIC rating designations. It is plausible that the properties (such as default rate, recovery, etc.) of the NAIC rating in practice are substantially different from those of Moody's rating used in the model development. With this in mind, we recommend an assessment of variation across NRSROs rating migration, default, and recovery rates, and across the credit cycle. If this is not possible because of, say, lack of historical data, Moody's Analytics recommends revisiting the use of the second-lowest NRSROs rating in assigning the NAIC designation.

5.5.2 Review Performed by Moody's Analytics

The Credit Rating Agency Reform Act (CRARA) of 2006 requires that entities that meet defined criteria register with the SEC as a condition of being designated as NRSROs. As a result, as of the beginning of 2019, there were ten rating agencies certified as NRSROs by the SEC. The NAIC adopted the Filing Exempt (FE) rule, granting any NRSRO that has registered with the SEC and has been designated an NRSRO the right to apply and provide credit rating services to the NAIC. Per (National Association of Insurance Commissioners, 2017) the NAIC SVO provides equivalent NAIC designation for nine NRSROs. Per (National Association of Insurance Commissioners, 2007) the FE process will calculate the second-lowest NRSROs rating in assigning the NAIC designation.

The use of multiple NRSROs in the context of model development requires a quantitative correspondence between credit ratings and a range of migration, default probabilities, and loss expectations, that needs to be better understood, recognizing NRSROs assess different aspects of credit risk. For example, Standard & Poor's recognizes that when, "assess[ing] the creditworthiness of an issuer, S&P Global Ratings evaluates the issuer's ability and willingness to repay its obligations in accordance with the terms of those obligations... Credit rating agencies may also assess recovery, which is the likelihood that investors will recoup the unpaid portion of their principal in the event of default. Some agencies incorporate recovery as a rating factor in evaluating the credit quality of an issue, particularly in the case of non-investment-grade debt. Other agencies, such as S&P Global Ratings, issue recovery ratings in addition to rating specific debt issues. S&P Global Ratings may also consider recovery ratings in adjusting the credit rating of a debt issue up or down in relation to the credit rating assigned to the issuer (Standard & Poor's, 2019)." Meanwhile, Moody's Investor Service, the rating agency arm of Moody's, takes the position that its "… ratings reflect both the likelihood of a default and the expected loss suffered in the event of default. Ratings are assigned based on a rating committee's assessment of a security's expected loss rate (default probability multiplied by expected loss severity)" (Moody's Investors Service, 2020 (3)).

The Dodd-Frank Act required the SEC to review the feasibility and desirability of NRSROs credit rating standardization, including quantitative correspondence between credit ratings and a range of default probabilities and loss expectations under standardized conditions of economic stress. In their report to congress, (Securities and Exchange Commision, 2012), the Commission recognized the number and uniqueness of rating scales and differences in credit rating methodologies used by credit rating agencies, and that NRSROs do not provide such a correspondence, because they base their credit ratings on a range of qualitative, as well as quantitative, factors. With this in mind, we recommend an assessment of variation across NRSROs rating migration, default, and recovery rates, and across the credit cycle. If this is not possible because of, say, lack of historical data, Moody's Analytics recommends revisiting the use of the second-lowest NRSROs rating in assigning the NAIC designation.

5.6 Climate Hazards and Emerging Risks

5.6.1 Summary of Moody's Analytics Significant Areas of Review and Recommendations

The C1 factors do not explicitly consider climate hazards or emerging risks (e.g., pandemic or cyber). These risks may not be explicitly incorporated into NRSRO ratings and may not be reflected in the historical data used in estimating the C1 factors. While climate hazards are particularly relevant for the likes of real estate and municipal credit, growing evidence suggests climate hazards and other emerging risks can be material for corporate credit[30]. Moody's Analytics recommends exploring the potential impact of climate hazards and emerging risks on C1 factors across asset classes.

5.6.2 Review Performed by Moody's Analytics

Climate hazards and emerging risks are drawing growing concerns from credit investors, financial regulators, and rating agencies. COVID-19 has demonstrated the rapid and cascading impacts of a global catastrophic risk that may not be explicitly considered in the NRSRO ratings and that may not be reflected in historical data. Pandemics — as well as climate hazards, debt crises, cyberattacks, and other events — are high-likelihood, high-impact risks (World Economic Forum, 2021).

Climate hazards have been recognized to impact municipal and commercial real estate credit. Climate hazards can be categorized into chronic and acute hazards. The impacts of the acute climate hazards, typically low-frequency and high-damage, may be worth special attention. Hurricane Harvey for example had Moody's downgrade Port Authority (Steinberg, 2018). Climate hazards are increasingly recognized as a risk for longer-dated corporate credit (Levy & Freitas, 2019). One study finds that eighteen sectors with $7.2 trillion issues have high inherent exposure to physical climate risks (Moody's Investors Service, 2020 (4)). The largest sectors in terms of rated debt include emerging market governments, regulated electric and gas utilities with generation, and integrated oil and gas companies. Moody's Investors Service has put efforts to include environment, social, and governance (ESG) risk assessment in the rating issuance and monitoring process. Moody's Investors Service launched a specialized ESG analytical team in March 2017 and published General Principles for Assessing Environment, Social and Governance Risks in January 2019. ESG factors were cited in half of public-sector rating actions taken in the 15 months through the first quarter of 2020 (Moody's Investors Service, 2020 (5)).[31] Likewise, S&P and Fitch have also been incorporating the ESG considerations into their ratings methodologies. For S&P, environmental and climate (E&C) concerns affected corporate ratings in 717 cases, or approximately 10% of corporate ratings assessments and resulted in a rating impact (an upgrade, downgrade, outlook revision, or CreditWatch placement) in 106 cases between July 2015 and August 2017 (S&P Global Ratings, 2017). Fitch Ratings developed an integrated scoring system, ESG Relevance Scores, which clearly displays how ESG factors impact individual rating decisions (Fitch Ratings, 2020).

Many regulators have been increasingly recognizing these risks. The European Central Bank (ECB), for example, speaks to "the number of catastrophes caused by natural hazards... Adjusting for inflation, overall economic losses… of USD 350 billion in 2018" (Lagarde, 2020). Governor Lael Brainard of the Federal Reserve speaks "we are already seeing elevated financial losses associated with… [the] frequency and intensity of extreme weather events" and cites the example of climate-related bankruptcy of Pacific Gas & Electric. She also points out "mortgages in coastal areas are vulnerable to hurricanes …" (Brainard, 2020). "Extreme weather…" is highlighted as one of the highest impact risks of the next decade in the Global Risks Report (World Economic Forum, 2020).

While being increasingly important considerations in NRSRO ratings, climate hazards and emerging risks may not be explicitly incorporated into historical NRSRO ratings nor reflected in the historical data used in estimating C1 factors. Moody's Analytics recommends exploring the potential impact of climate hazards and emerging risks on C1 factors across asset classes.

[30] See Moody's Analytics Research Paper for an empirical assessment of financial impacts of climate-related hazard events (Ozkanoglu, Milonas, Zhao, & Brizhatyuk, 2020)
[31] Other factors such as changes in economic growth, budget deficits or leverage metrics are also considered. When a rating action cites an ESG issue as a material credit consideration, it does not necessarily mean that the issue was a key driver of the rating action.

6 Suggested Next Steps

As discussed in the Executive Summary, this report documents Moody's Analytics objective assessment of the modeling process, the development of assumptions from underlying experience, and the adjustments to reflect diversification of individual company portfolios used in investment risk factors for fixed income assets. The report recognizes that C1 factors have potential implications for business decisions that can ultimately impact solvency. Moreover, Moody's Analytics is aware of the significant effort involved in a broader redesign of C1 factors and understands the original scope was limited to model parameter updates and increased C1 factor granularity in the C1 Factor Proposal. Moody's Analytics appreciates that since the original C1 factors were released in 1992, life insurance exposure to credit has increased in size and complexity, and that new data and techniques are now available that can better describe credit risk.

With these aspects in mind, we suggest a phased-in approach, whereby, targeted aspects of the model development are addressed immediately, recognizing that a broader redesign of C1 factors is also in order. Both the immediate changes, as well as the broader redesign, should have stakeholders prioritize items from **Table 1**, **Table 2**, and **Table 3**, along with potential items outside the scope of this report, recognizing that: (1) changing only one aspect must be done cautiously, given the interconnectedness of portfolio models, and that (2) the objective of allowing C1 factors and their impact on business decisions is to align with prudential management of solvency.

As discussed, the tight April deadline limits the possible items that can be revised during the first phase, focusing on the "slope" of charges across credit ratings and the portfolio adjustment function. The revisions should be approached in conjunction with stakeholders iteratively, as follows:

- Review and prioritize modifications to the proposed rules, along with the current rules as a point of reference.
- Assess and agree on performance criteria, along with possible data sources and methodologies.
- Propose updated model parameters and C1 factors, recognizing benchmarking and validation concerns including model limitations, and adhering to sound model risk management guidelines (Board of Governors of the Federal Reserve System and Office of the Comptroller of the Currency , 2011).
- Assess implications for solvency across the life insurance industry.

In addition, Phase 1 should include an articulation of model limitations related to the other items referenced in this document at a level of detail and adhering to a timeline to be determined jointly with stakeholders.

The Phase 2 broader redesign should start as soon as practical, prior to completion of Phase 1. It would not be completed in 2021, recognizing the lead time needed for data collection and research. It should be approached in conjunction with stakeholders in an iterative manner, as follows:

- Obtain clarity on the desired level of:
  - Model complexity (e.g., issuer concentration)
  - Granularity (e.g., differentiating across asset risks)
- Assess cost implications
  - Resources, including personnel, to develop and implement models within a sound model risk management framework
  - Data collection
  - Model monitoring and model re-development
- Articulate governance — potentially impacting organizational structure at insurance companies and NAIC
  - Control mechanisms through policies and procedures associated with model development, validation, implementation, and use
- Propose redesigned C1 factors
  - Assess and agree on performance criteria, along with possible data sources and methodologies
  - Propose updated model and C1 factors, recognizing benchmarking and validation concerns, including model limitations, and adhering to sound model risk management guidelines (Board of Governors of the Federal Reserve System and Office of the Comptroller of the Currency , 2011)
  - Assess implications for solvency across the life insurance industry

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MORTGAGE BANKERS ASSOCIATION

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January 29, 2021

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RE: Re-alignment of RBC Guidance and INT 20-03 Modification Dates

Dear Mr. Barlow and Working Group Members:

The Mortgage Bankers Association[1] and the American Council of Life Insurers[2] respectfully recommend that the Life Risk-Based Capital Working Group (LRBCWG) modify its *Additional Guidance* on the Financial Condition (E) Committee's *Guidance for Troubled Debt Restructurings* (RBC Guidance) to align the modification period with revised INT 20-03, *Restructuring Due to COVID -19*.

Troubled debt restructurings (TDR) relief under both the RBC Guidance and INT 20-03 was issued in furtherance of the E Committee's statement of support for "the use of prudent loan modifications that can mitigate the impact of COVID-19."[3] Accordingly, the E Committee, Statutory Accounting

[1] The Mortgage Bankers Association (MBA) is the national association representing the real estate finance industry, an industry that employs more than 280,000 people in virtually every community in the country. Its membership of over 2,300 companies includes all elements of real estate finance: mortgage companies, mortgage brokers, commercial banks, credit unions, thrifts, REITs, Wall Street conduits, 70 life insurance companies engaged in real estate finance, and others in the mortgage lending field. For additional information, visit MBA's website: www.mba.org.

[2] The American Council of Life Insurers (ACLI) is the leading trade association driving public policy and advocacy on behalf of the life insurance industry. 90 million American families rely on the life insurance industry for financial protection and retirement security. ACLI's member companies are dedicated to protecting consumers' financial wellbeing through life insurance, annuities, retirement plans, long-term care insurance, disability income insurance, reinsurance, and dental, vision and other supplemental benefits. ACLI's 280 member companies represent 95 percent of industry assets in the United States. Learn more at www.acli.com

[3] See RBC Guidance, p. 1 ("This guidance is being issued by the Financial Condition (E) Committee to all U.S. insurers filing with the NAIC in an effort to encourage insurers to work with borrowers who are unable, or may become unable to meet their contractual payment obligations because of the effects of COVID-19. The Committee, which is the NAIC parent committee of all the solvency policy making task forces and working groups of the NAIC, supports the use of prudent loan modifications that can mitigate the impact of COVID-

Principles Working Group (SAPWG) , and LRBCWG have taken actions necessary to align the RBC Guidance and INT 20-03 modification periods for the reporting periods ending June 30, September 30, and December 31, 2020.

On January 25, 2021, SAPWG revised the modification period under INT 20-03 to conform to the TDR provision of the CARES Act, as amended by the *Consolidated Appropriations Act, 2021*, which was signed into law on December 27, 2020. As a result, INT 20-03 now applies to modifications that occur during "the period ending on the earlier of January 1, 2022 or the date that is 60 days after the date on which the national emergency concerning the novel coronavirus disease (COVID–19), outbreak declared by the President on March 13, 2020 under the National Emergencies Act terminates." In contrast, the modification period under the RBC Guidance ended December 31, 2020.

To re-align modification periods under RBC Guidance with INT 20-03, we recommend that the LRBCWG revise its *Additional Guidance* dated October 9, 2020, as follows:

> **<u>Origination Date, Valuation Date, Property Value, and 90 Days Past Due</u>**
>
> For purposes of the Description/explanation of item in the Risk-Based Capital Reporting Instructions for Date of Origination (2), Property Value (20), Year of Valuation (21 and by reference Quarter of Valuation - 22), and 90 Days Past Due? (29), no changes to these values are required for any COVID-19 related modifications that occur during ~~2020~~ the period ending on the earlier of January 1, 2022 or the date that is 60 days after the date on which the national emergency concerning the novel coronavirus disease (COVID–19), outbreak declared by the President on March 13, 2020 under the National Emergencies Act terminates. This guidance is consistent with the Financial Condition (E) Committee Guidance for Troubled Debt Restructurings for March 31 - September 30 Statutory Financial Statements and Related Interim Risk-Based Capital Filings (where required) (June 12, 2020) and Question and Answer issued by the NAIC but extended for COVID19 modifications that occur through the end of ~~2020~~ the period described above.

To facilitate insurer's planning and reporting activity, we urge LRBCWG to make such a revision as early as possible during the reporting period ending March 31, 2021.

Respectfully,

Mike Flood

Paul S. Graham, III

Attachment: INT 20-03. *Troubled Debt Restructuring Due to COVID-19* (revised January 25, 2021)

cc: Dave Fleming, NAIC Senior Insurance Reporting Analyst

19."); see also INT 20-03, p. 1, INT 20-03 Issue, para. 3 (citing the same language as part of the SAPWG rational for issuing INT 20-03).

NAIC National Association of Insurance Commissioners & The Center for Insurance Policy and Research

To: All Insurers
From: Life Risk-Based Capital (E) Working Group
RE: Guidance for Troubled Debt Restructurings for December 31, 2020 and Interim Risk-Based Capital Filings (where required)
Date: October 9, 2020, Revised February 11, 2021

Additional Guidance Adopted by the Life Risk-Based Capital Working Group

The Financial Condition (E) Committee delegated to the Life Risk-Based Capital (E) Working Group certain questions that arose as part of its June 12 memorandum. Under that delegation, the Working Group adopted the following guidance.

Construction Loans

For purposes of Note 4 to the Risk-Based Capital Reporting Instructions, government-mandated construction delays due to COVID-19 that occur at any time during 2020 are not "construction issues." This guidance would apply to all mortgages and not just those mortgages where a COVID-19 modification occurred.

Origination Date, Valuation Date, Property Value, and 90 Days Past Due

For purposes of the Description/explanation of item in the Risk-Based Capital Reporting Instructions for Date of Origination (2), Property Value (20), Year of Valuation (21 and by reference Quarter of Valuation - 22), and 90 Days Past Due? (29), no changes to these values are required for any COVID-19 related modifications that occur during the period ending on the earlier of January 1, 2022 or the date that is 60 days after the date on which the national emergency concerning the novel coronavirus disease (COVID–19), outbreak declared by the President on March 13, 2020 under the National Emergencies Act terminates~~2020~~. This guidance is consistent with the Financial Condition (E) Committee Guidance for Troubled Debt Restructurings for March 31 - September 30 Statutory Financial Statements and Related Interim Risk-Based Capital Filings (where required) (June 12, 2020) and Question and Answer issued by the NAIC but extended for COVID-19 modifications that occur through the end of the period described above~~2020~~.

Contemporaneous Property Values

For purposes of computing the Contemporaneous Property Value (40) for any period ending in 2020, an insurer may use the average of the NCREIF Price Index as of 12/31/2019 and the 2020 NCREIF Price Index for the Price Index current value. This guidance applies to all mortgages and not just those mortgages where a COVID-19 modification occurred, and it applies for the filings for any period ending in 2020 only and not subsequent years.

Net Operating Income

For purposes of the NOI inputs at (14), (15), (16), and the computation of a Rolling Average NOI at (36), an insurer may report 2020 NOI (i.e., NOI for any 12-month fiscal period ending after June 30, 2020 but not later than June 30, 2021) as the greater of: (1) actual NOI as determined under the CREF-C IRP Standards or (2) 85% of NOI determined for the immediate preceding fiscal year's annual report. This guidance with respect to 2020 NOI applies to the application of the 2020 NOI in risk-based capital reporting for 2021, 2022, and 2023. In cases where an insurer reports 85% of 2019 NOI as the 2020 NOI input, the insurer should retain information about actual 2020 NOI in its workpapers so that the information can be readily available to regulators.

Related Accounting Guidance & Updates

Please see the following for both related accounting guidance and updates to this guidance via Q&A. https://content.naic.org/cmte_e_lrbc.htm
(Please see related documents tab)

Questions

Any questions on this guidance should be directed to Dave Fleming by e-mail at dfleming@naic.org.

National Association of Insurance Commissioners

The Center for Insurance Policy and Research

To: All Insurers
From: Life Risk-Based Capital (E) Working Group
RE: Additional Guidance for Troubled Debt Restructurings ~~for December 31, 2020 and Interim Risk-Based Capital Filings (where required)~~
Date: ~~October 9, 2020~~February 11, 2021

Additional Guidance Adopted by the Life Risk-Based Capital Working Group

In response to action taken by ~~T~~the ~~Financial Condition~~Statutory Accounting Principles (E) ~~Committee~~ Working Group ~~delegated to the Life Risk-Based Capital (E) Working Group certain questions that arose as part of its June 12 memorandum.~~ which addressed modification of the original CARES Act to extend the provisions for temporary relief from troubled debt restructurings~~Under that delegation~~, the Working Group adopted the following modification to its October 9 ~~-~~guidance. This modified guidance is to address only the category shown as the remainder of the October 9 document is unchanged.

~~**Construction Loans**~~

~~For purposes of Note 4 to the Risk-Based Capital Reporting Instructions, government-mandated construction delays due to COVID-19 that occur at any time during 2020 are not "construction issues." This guidance would apply to all mortgages and not just those mortgages where a COVID-19 modification occurred.~~

Origination Date, Valuation Date, Property Value, and 90 Days Past Due

For purposes of the Description/explanation of item in the Risk-Based Capital Reporting Instructions for Date of Origination (2), Property Value (20), Year of Valuation (21 and by reference Quarter of Valuation - 22), and 90 Days Past Due? (29), no changes to these values are required for any COVID-19 related modifications that are captured within *INT 20-03: Troubled Debt Restructuring Due to COVID-19* or *INT 20-07: Troubled Debt Restructuring of Certain Debt Instruments Due to COVID-19.* ~~occur during 2020. This guidance is consistent with the Financial Condition (E) Committee Guidance for Troubled Debt Restructurings for March 31 - September 30 Statutory Financial Statements and Related Interim Risk-Based Capital Filings (where required) (June 12, 2020) and Question and Answer issued by the NAIC but extended for COVID-19 modifications that occur through the end of 2020.~~

~~**Contemporaneous Property Values**~~

~~For purposes of computing the Contemporaneous Property Value (40) for any period ending in 2020, an insurer may use the average of the NCREIF Price Index as of 12/31/2019 and the 2020 NCREIF Price Index for the Price Index current value. This guidance applies to all mortgages and not just those mortgages where a COVID-19 modification occurred, and it applies for the filings for any period ending in 2020 only and not subsequent years.~~

~~**Net Operating Income**~~

~~For purposes of the NOI inputs at (14), (15), (16), and the computation of a Rolling Average NOI at (36), an insurer may report 2020 NOI (i.e., NOI for any 12-month fiscal period ending after June 30, 2020 but not later than June 30, 2021) as the greater of: (1) actual NOI as determined under the CREF-C IRP Standards or (2) 85% of NOI determined for the immediate preceding fiscal year's annual report. This guidance with respect to 2020 NOI applies to the application of the 2020 NOI in risk-based capital reporting for 2021, 2022, and 2023. In cases where an insurer reports 85% of 2019 NOI as the 2020 NOI input, the insurer should retain information about actual 2020 NOI in its workpapers so that the information can be readily available to regulators.~~

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Questions

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