RESIDUAL TRANCHE RISK ANALYSIS

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A business of Marsh McLennan

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Contents

1. Executive Summary

This report presents a quantitative analysis of the relative risk of residual tranches of Asset-Backed Securities (ABS). We analyzed the potential losses under historically-calibrated stress scenarios, considering both “mid-tail” (~95th percentile) and “deep-tail” stress scenarios, on a portfolios of residual tranche deals. This analysis then enables us to compare the decline in valuation of these assets to the losses experienced by other asset classes in the corresponding stress periods.

In Section 1, we observe the growing significance of structured products to insurer balance sheets. We then outline the primary objectives of this report: to conduct a fact-based assessment of ABS residual tranches that enables objective comparisons to other common assets and provides data to help inform the calibration of the capital charge of residual tranches. We then outline the guiding principles on which we based our analytical approach, including aligning our approach with the approaches taken by the NAIC in its calibration of the capital charges for other investment assets.

In Section 2, we describe our methodological approach to assessing the risk associated with residual tranches ABS deals. We begin by describing the process by which we determine the scope of assets for our analysis, namely CLOs, auto loans, and student loans, and the selection of the specific deals in our analysis. Next, we present our modeling approach, a scenario-based approach that considered the cash flows available to these tranches. We then describe, for each asset type, the method used to calibrate our base scenario, mid-tail (95th percentile), and deep-tail stress scenarios, including the choice of historical data. We conclude this section with a discussion of the balance sheet treatment of residual tranches and the output metrics examined.

In Section 3, we discuss the results of our analysis. Our analysis focused on the decline in fair-value, measures as the net present value of the cash flows available to the residual tranche under each scenario. We find that these losses vary, among other factors, based on the underlying collateral and residual thickness. For the asset types examined, losses at a portfolio-level ranged from -42% for broadly syndicated CLOs to -6% for prime auto loans under mid-tail scenario.

In Section 4, we compare the observed losses, on both an aggregate basis and for each asset type, with those of other common assets, specifically common stock, commercial real estate, and corporate bond. We find that ABS residual tranches realize lower losses on a portfolio-level than does common stock under corresponding levels of macroeconomic stress, though ABS residual tranches realize greater losses than do commercial real estate and low-rated corporate bonds.

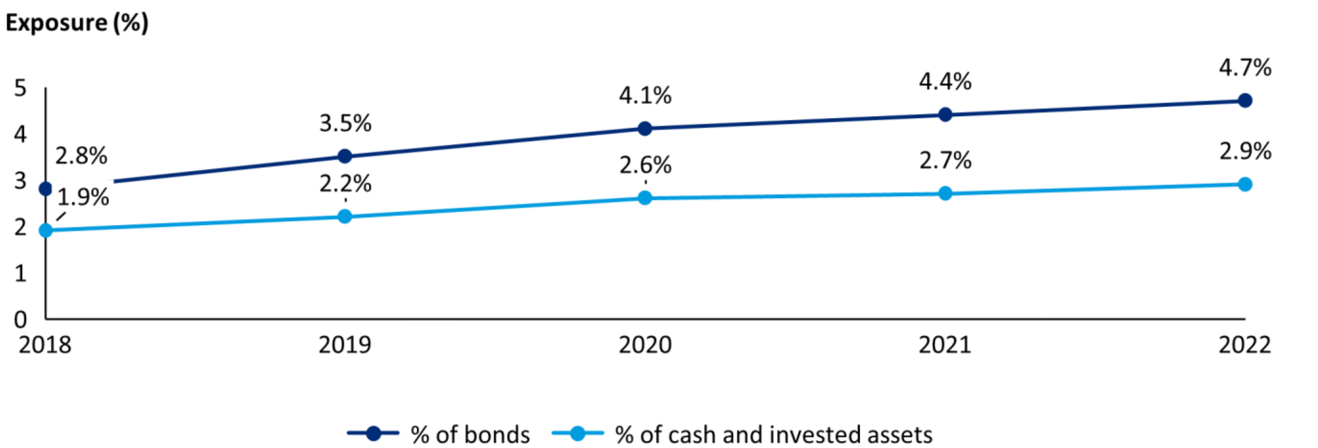
The subsequent report is intended to provide a data-driven and objective analysis to bring fact-based insight into an under-researched topic within the insurance industry.

2. Introduction

2.1. Context

In recent years, insurance companies have increased their allocation assets to structured products – including Asset-Backed Securities (ABS) – in efforts to build an attractive investment portfolio to support policy obligations. These insurers strategically allocate a portion of their assets to these securities, typically with the dual goals of enhancing their investment returns and diversifying their portfolio by accessing a broader spectrum of investment opportunities. Figure 1[1] illustrates this growth in CLO exposure across insurers as a percentage of bonds and of cash and invested assets. The complexity of structured ABS, particularly the residual tranches, have raised concerns about the value of these assets during stress periods.

Figure 1: US insurer CLO exposure, % (annual 2018-2022)



Structured products are financial instruments crafted to offer investors exposure to a wide range of underlying collateral including, but not limited to, corporate loans, auto loans, and student loans. The specific mechanics of these products have evolved over time and vary by sector. However, the products most often have different tranches, ranging from most-senior (often AAA-rated) to most junior (residual equity), to meet the risk appetite and return requirements of different types of investors. The relative risk of the tranches is largely determined by the order of the cash flows paid from the underlying collateral; that is, senior tranches receive cash flows first, and subsequent payments cascade down the deal's "waterfall" until they reach the equity tranche, which is paid last. This payment hierarchy ensures that investors in different tranches are treated fairly and receive their payments according to the predetermined order.

The complexity of structured ABS, particularly the residual tranches, combined with their increased prevalence, has raised concerns about the potential losses on these assets during stress periods and resulted in an increase in scrutiny from regulators and other industry stakeholders. The NAIC recently begun to undertake a broader review in 2023 of its capital approach for structured products, including ongoing efforts around CLOs. However, as an intermediate measure, it has proposed applying a 45% capital charge for residual

[1] U.S. insurer CLO exposure to bonds and cash & invested assets from 2018 - 2022 (%): *NAIC, "Continued Double-Digit Increase in U.S. Insurers' Collateralized Loan Obligation Exposure in 2022" (2022)*

tranches. The NAIC has indicated an interest in receiving quantitative analysis of the risk profile of residual tranches from industry participants to inform its calibration of the factor applied to these assets.

2.2. Objective of report

In this report, we focus on the residual equity tranche of asset-backed securities (ABS), which generally have the lowest-priority entitlement to cash flows within the broader deal waterfall. Limited rigorous quantitative analysis has been performed to evaluate the risk associated with these assets and support a calibration of a capital charge for use within the NAIC's Risk-Based Capital framework. This report seeks to remedy this gap by:

- Applying a fact-based assessment to evaluate the risk profile of residual tranches of ABS
- Enabling an objective comparison of the risk profile of residual tranches to other commonly held assets, such as equities, real estate, or corporate bonds
- Providing data to help inform the calibration of the capital charge of residual equity tranches

2.3. Guiding Principles

We designed our analytical approach based on three guiding principles:

- First, our modeling approach was, to the extent possible, based on the NAIC's own methodology to calibrate RBC charges for other investment assets
- Second, our approach aimed to capture the substantial variation in the underlying collateral as well as structuring between asset classes.
- Third, we designed our approach to be based on projected cash flows isolating losses due to credit risk, as opposed to other risks such as interest rate or liquidity risk

2.4. Precedents

Historically, the NAIC has used a range of similar methodologies to calibrate the capital charge of different asset classes. To inform the analysis undertaken in this paper, we surveyed these approaches to identify the methodologies and approaches applied. **Table 1** shows the approach the NAIC has taken in determining the RBC charges for corporate bonds, equities, and real estate.

Table 1: Select RBC charge calibration approaches

Asset		RBC charge	Timing	Severity	Calibration approach
Corporate bonds	NAIC 1	0.16%-1%	10-year loss horizon	96^{th} percentile (for the entire bond portfolio)	Simulation (cumulative defaults under 2,000 stochastic trials)
	NAIC 2	1%-2%			
	NAIC 3	3%-6%			
	NAIC 4	7%-12%			
	NAIC 5	16%-30%			

	NAIC 6	30%			
Equities		30%[2]	2-year loss horizon	94^{th} percentile	Historical data (S&P 500 from 1960-1991)
Real Estate		11%-13%	2-year loss horizon (to capture economic cycle)	96.8^{th} percentile confidence level	Historical data (national database of real property and mortgage securities data from 1978-2020)

Based on this survey, we identified five components of the prior calibration efforts that informed our methodological approach:

- Capital charges were calibrated at a $94\text{-}96^{th}$ percentile
- Calibration was based on historical data (period and length vary by asset class)
- Calibration considered a multi-year window to capture full length of an adverse event
- Losses were measured on an aggregated basis for the relevant asset class, by examining performance of an index or diversified portfolio
- Metrics used to measure losses, while varying, reflect the balance sheet treatment for asset type

Our methodology is consistent with these observations by:

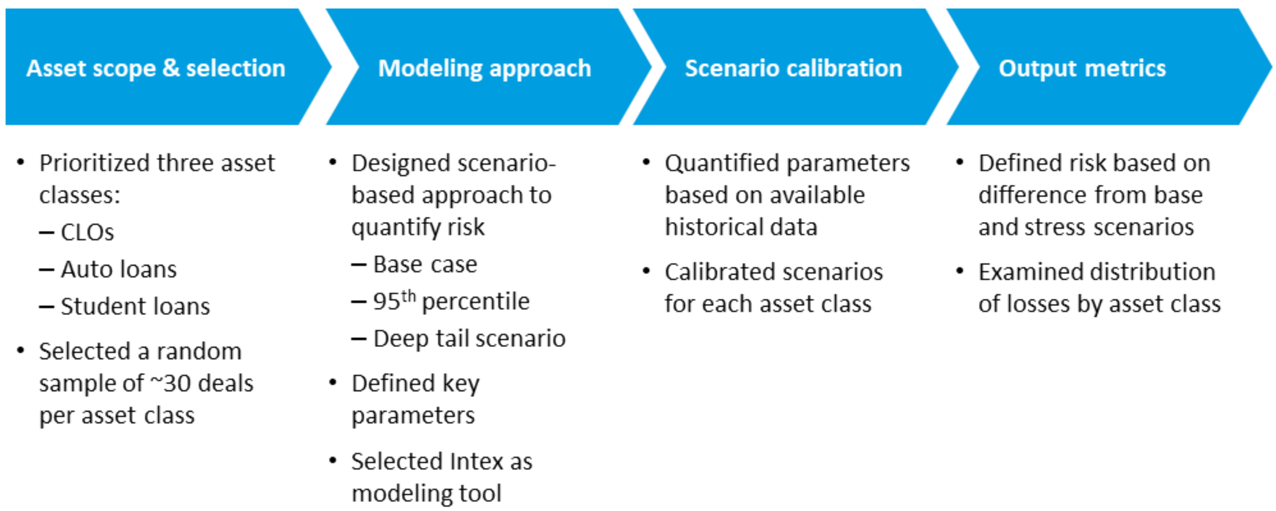
- Evaluating losses at the 95^{th} percentile event or “mid-tail” (vs. Deep-tail)
- Using historical experience for underlying collateral to calibrate potential losses
- Calibrating losses over the full credit cycle
- Considering aggregate performance of a representative portfolio of assets
- Defining risk metrics consistent with balance sheet treatment

[2] For $\beta = 1$

3. Methodology

We structured our methodological approach into four primary steps. First, we determined the asset scope and selection of deals for modeling. Second, we determined our modeling approach, which utilized a scenario-based methodology to quantify the relative risk of these assets. Third, we calibrated specific stress scenarios to simulate against these deals. Fourth, we defined the output metrics to measure the impact of these stress scenarios on the portfolio of in-scope deals. **Figure 2** provides an overview of this approach.

Figure 2: Overview of approach



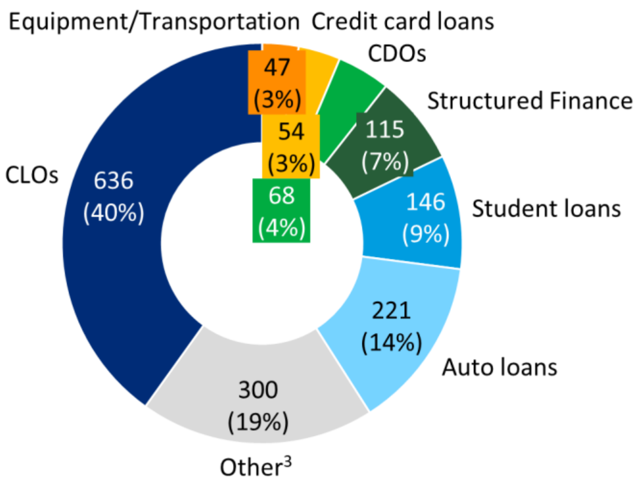
The following sections provide additional information on the asset scope & selection, modeling approach, scenario calibration, and chosen metrics.

3.1. Asset Scope & Selection

3.1.1. Asset Scope:

We selected three classes of ABS on which to focus our analysis: CLOs, auto loans, and student loans. These classes were chosen as they compose the largest share of outstanding ABS volume. We further segmented CLOs into Middle-Market (MM) and Broadly Syndicated Loan (BSL) CLOs and auto loan ABS into prime and subprime auto loan ABS. **Figure 3** illustrates the total ABS outstanding volume by asset class.

Figure 3: ABS total outstanding volume by asset class, $B (%) (2021)[3]



The figure shows that CLOs represent the plurality of the total US ABS market (40%), while auto and student loan ABS represent the next largest shares among individual asset classes (14% and 9%, respectively). Asset classes such as Collateralized Debt Obligations (CDO), credit card loans, and equipment/transportation represent a small share of the ABS market (4%, 3%, and 3%, respectively).

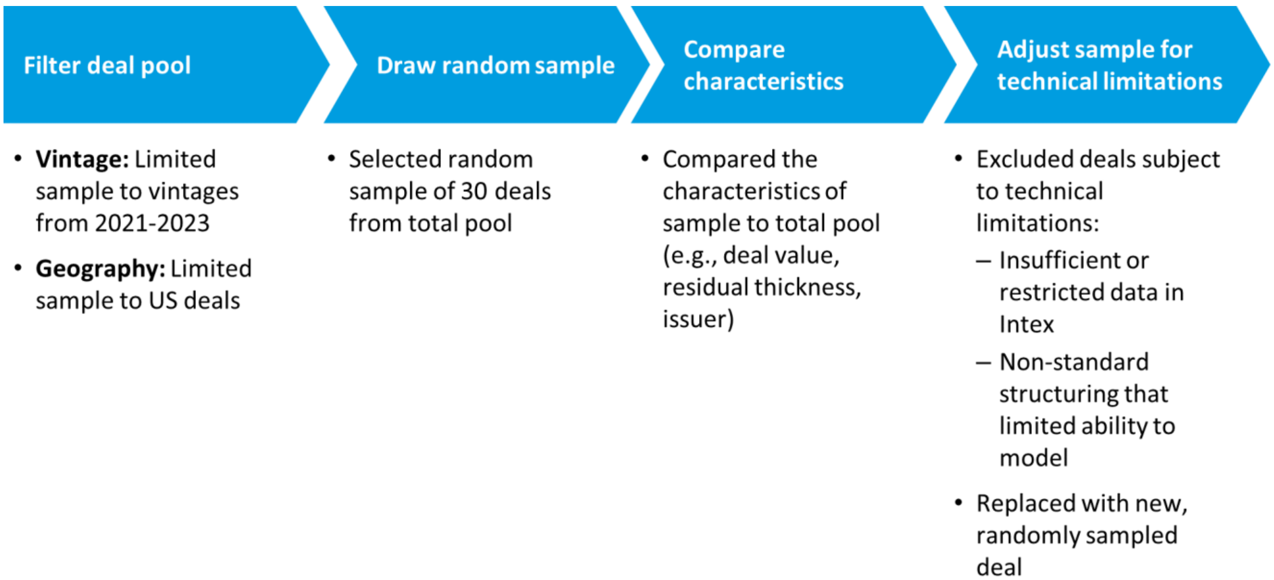
We examined the two largest segments of the CLO market: Middle-Market (MM) and Broadly Syndicated Loan (BSL) CLOs (which make up roughly 90% of the CLO market). Similarly, we examined the two largest segments of the auto loan ABS market: prime and subprime (which make up roughly 75% of the Auto ABS market).

[3] ABS total outstanding volume by asset class in 2021 (%): *SIFMA US ABS Securities*

3.1.2. Selection Process:

For each subclass of ABS, we followed the steps below in **Figure 4** to select an appropriate set of securities to model.

Figure 4: Overview of asset selection process



We selected a random sample of deals to model within each subclass: CLOs (both MM and BSL), auto loans (both prime and subprime), and student loans. The selection process was consistent across all the asset classes in scope. This process, although random, controlled for two factors: vintage and geography. First, we limited our sample to vintages originated between 2021 and 2023. This approach was taken to reflect current deal structures and because these deals comprise a greater portion of the outstanding issuance – and will thus be most relevant to future implementations of proposed capital rules. Additionally, we only included US deals, as these are the most relevant for US-based life insurers. After applying the two filters to the broader deal universe of each respective asset class, we selected a random sample of thirty deals from the total pool of deals modeled in Intex[4]. This sample size was chosen to achieve sufficient statistical breadth while maintaining a manageable volume of deals. We assumed that the process of random sampling would yield a statistically representative sample. After selecting a random sample of deals, we compared summary statistics of our sample with the full universe of US deals originated between 2021 and 2023, which can be seen in Section A.4 of the Appendix, and in all cases observe similar distributions across the examined characteristics. Finally, we adjusted the sample as needed on a case-by-case basis, due to either technical constraints (e.g., insufficient or restricted data on the deal in Intex) or individual deal characteristics (e.g., nonstandard structuring). **Table 35** provides a list of all deals excluded from our analysis.

[4] See Section A.4 of appendix for summary statistics of sample compared to total deal universe

3.2. Modeling Approach

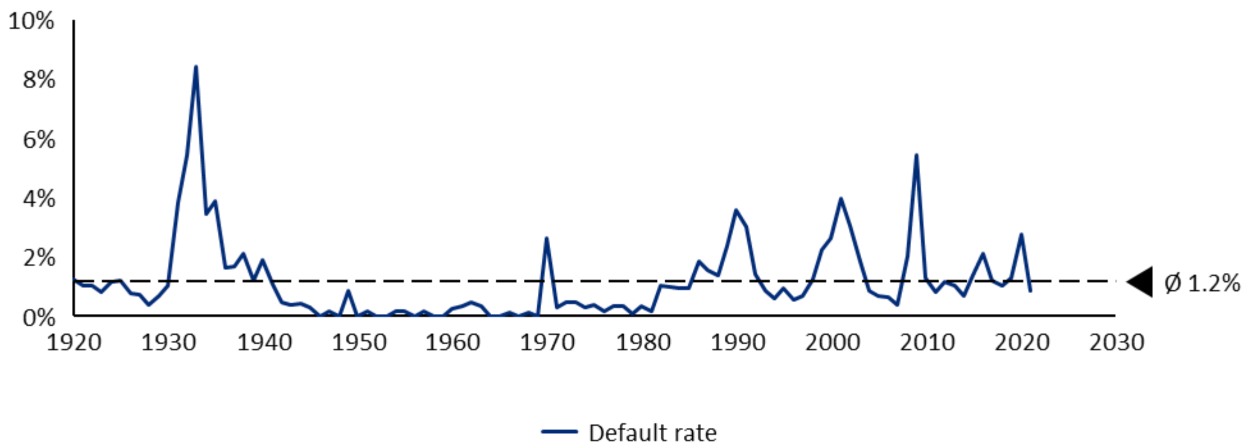
We utilized a scenario-based approach to measure the relative risk of ABS residuals across simulated base and stress cases in Intex. We chose to use Intex due to the breadth of ABS deals accessible within the platform, the thorough coverage of the specific legal terms of our in-scope ABS, and Intex's capability to generate resulting cash flows of deals based on assumptions about the underlying collateral behavior.

Several decisions guided our modeling approach:

- We evaluated multiple historical, stress scenarios which was consistent with NAIC's methodology of calibrating the RBC charges of other asset classes based on observed historical experience (e.g., equities and real estate). We did not use a stochastic methodology to estimate the impact of stress on the value of residuals because of a lack of historical data of the underlying investment sufficient to make such a complex statistical models robust.
- We designed three stress scenarios to simulate the impact of a range of severities in adverse economic conditions on the in-scope asset classes.
- We applied stress to the underlying collateral of the assets rather than the bonds comprising the ABS. This is because the value of equity tranches is derived from the value of the underlying assets, for which there is more robust available data.
- We determined the severity of our scenarios based on several factors. To maintain consistency with how the NAIC has calibrated capital charges historically, we created two stress scenarios of approximately 95th percentile severity[5], considering relative historical and economic significance events with different default timing profiles. In addition, to understand the potential for losses in a deep-tail event, we also considered a "Deep-tail" scenario, modeled after the Great Depression, and intended to reflect approximately a 99th percentile severity. We did not have sufficient data to conduct a robust statistical analysis to directly model the severity for this scenario. Rather, we used default rates of Corporate Bonds from Moody's Investors Service as a proxy for increase in credit losses under the Deep-tail scenario. **Figure 5** illustrates annual corporate bond default rates from 1920-2021. During this approximately 100-year period, we observed four large spikes in default rates: the Great Depression (1931-1940), Savings & Loan Crisis (1986-1992), the Dot-Com Crisis (1998-2003), and the Global Financial Crisis (2008-2010). This experience suggests that the spikes observed in these events are approximately 1-in-20 events in terms of excess defaults. The Great Depression, by contrast, is closer to a 1-in-100 event in terms of excess defaults.

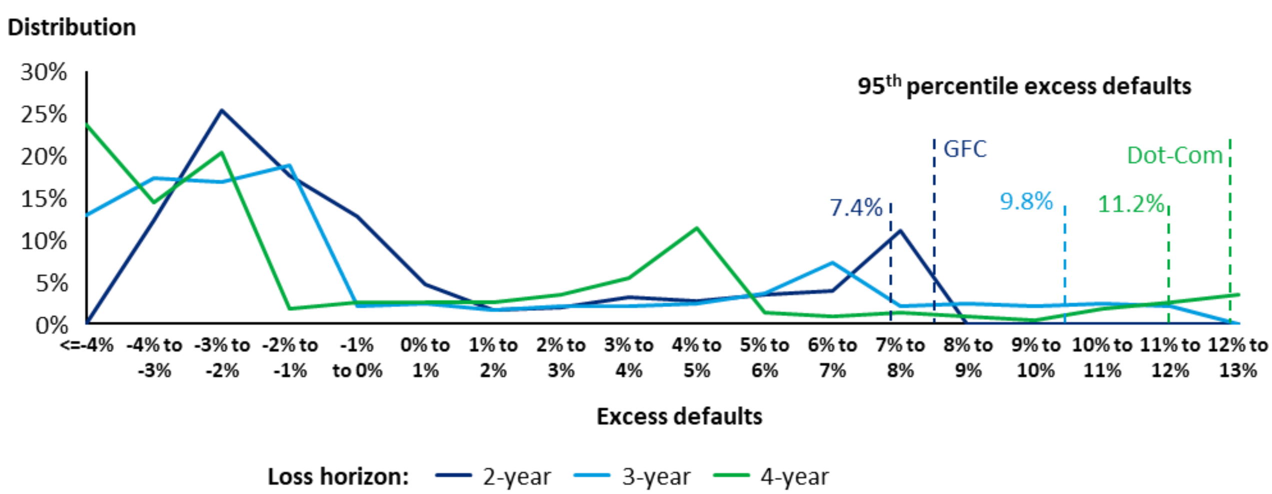
[5] This approach differs from the methodology that the American Academy of Actuaries is applying in its work on CLOs, which uses CTE90 as the risk metric. For a normal distribution, CTE90 is equivalent to approximately the 95th percentile. The choice of CTE90 reflected in part concerns around the performance of residual tranche ABS in more severe, or "Deep-tail" scenarios. The analysis in this report also considers the performance of these assets in a deep-tail scenario.

Figure 5: US corporate bond default rates, % (annual 1920-2021)[6]



- Additionally, we observed that excess default losses (i.e., principal in default above the long-term average) for the US LSTA 100 were both higher than 95th percentile excess default losses for the relevant loss horizons (2 years for GFC and 4 years for Dot-Com bubble), as depicted in **Figure 6**. This analysis applies a similar approach to that used by the NAIC in its calibration of the capital charges for common stock and real estate, namely determining the percentile losses based on a rolling window, and the approach was chosen to reflect our guiding principle of consistency. While this analysis is based on a 24-year time series, it supports use of the GFC and Dot-Com stresses as suitable 95th percentile stress scenarios.

Figure 6: US LSTA 100 95th percentile excess defaults by loss horizon, % (1999-2022)[7]



[6] Annual U.S. corporate bond default rates from 1920 - 2021 (%): *Moody's Investors Service, "Corporate Default and Recovery Rates" (2021)*

[7] Excess defaults are defined as the defaults in excess of the long-term average (1999 – 2022). The 95th percentile excess defaults are calculated for each loss horizon from 1999-2022 (%): *S&P, U.S. LSTA*

- Our selection of parameters was determined based on relevance to the underlying assets being stressed. We used available historical data to derive parameters which we used as inputs in Intex. We used these parameters to build stress scenarios and applied those scenarios to a portfolio of randomly selected deals within each in-scope asset class. The subsequent section provides more detail on specific parameters used for each segment.

3.3. Scenario Calibration

This section discusses the methodology used to calibrate scenario-level modeling parameters, including default rates, recovery rates, prepayment rates, recovery lags, delinquency rates (for auto loans), and reinvestment period assumptions. In the calibration of the scenarios, the intention was to reflect both the severity and duration of a Mid-tail (~95 percentile) and Deep-tail event. As such, we consider the level of excess defaults over the credit cycle. A limitation of this approach is that no historical time series on the relevant underlying collateral included a Deep-tail event (that is, an event of similar severity to the Great Depression). As a result, we relied on the experience of corporate bonds during this period to serve as a proxy for the potential performance of the underlying collateral and applied a similar increase in default rates and/or level of excess defaults.

3.3.1. CLOs

Table 2 shows the calibration of scenario-specific modeling parameters. With the exception of the default rate, which was calibrated separately to account for difference in the credit quality of the underlying loans, common parameters were used for the BSL and MM segments.

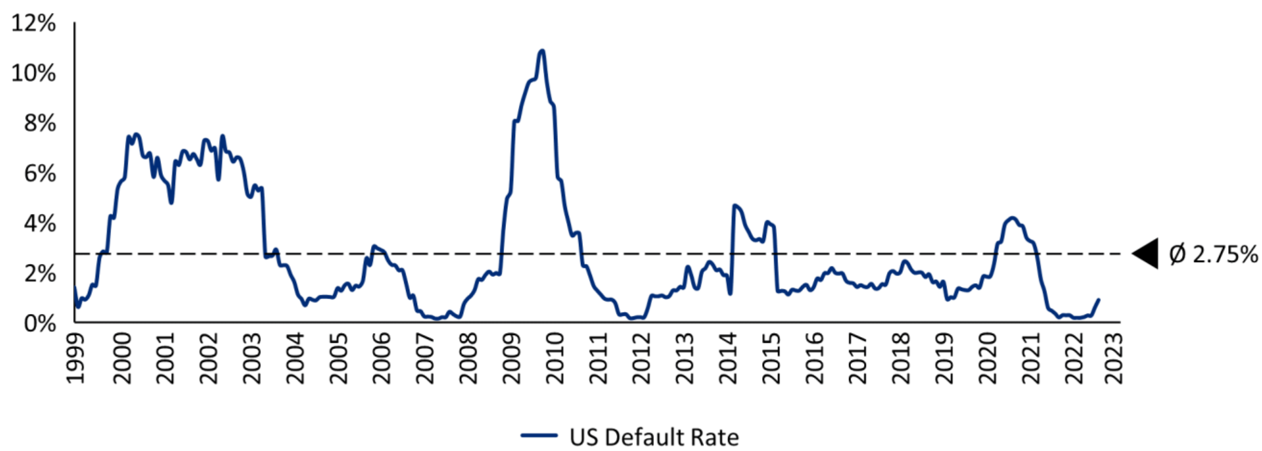
Table 2: Scenario-level parameters for CLOs

	Base	**Mid-tail (~95th percentile)**		
Parameter		**Dot-Com**	**GFC**	**Deep-tail**
Peak default rate *(BSL)*	2.6%	2.7x multiplier *(peak)*	3.9x multiplier *(peak)*	5.9x multiplier *(peak)*
Peak default rate *(MM)*	4.1%			
Excess defaults *(BSL)*	N/A	11.9%	7.6%	33.7%
Excess defaults *(MM)*	N/A	18.4%	11.8%	52.2%
Recovery rate	66.4%	61.1%	58.0%	55.9%
Prepayment rates	24.8%	18.4%	14.0%	10.0%
Recovery lag	18 months	18 months	18 months	18 months
Reinvestment	None	None	None	None

3.3.1.1. Baseline scenario

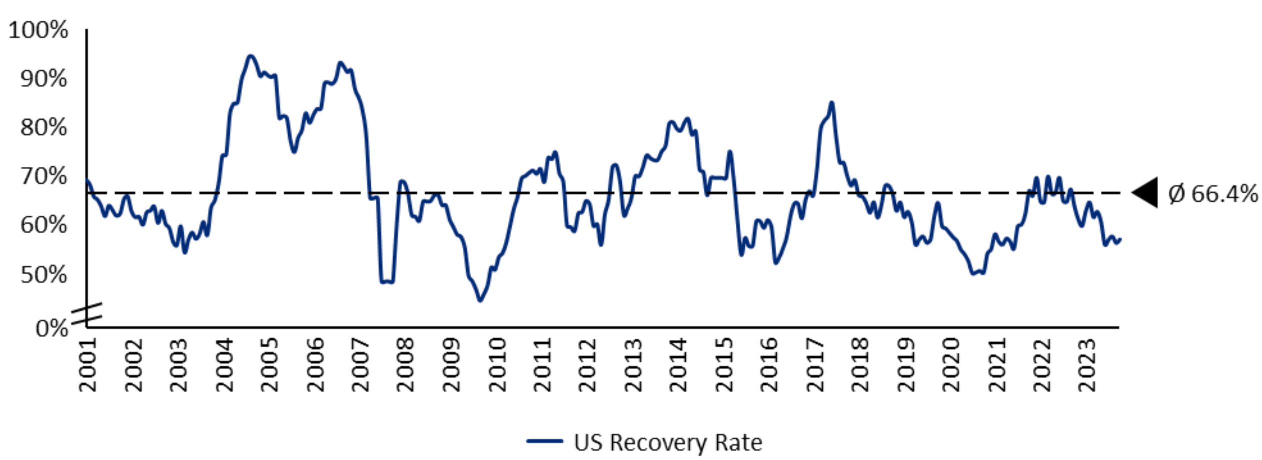
We constructed a baseline scenario for CLOs by calculating long-term averages of the applicable parameters based on available historical data. For default rates, we primarily relied on historical data from the S&P Loan Syndications and Trading Association (LSTA) 100 index series from 1999-2022, which is shown in **Figure 7** below. Additional adjustments were made to account for differences in the underlying collateral quality of BSL and MM and discussed later.

Figure 7: Default rates, % of principal (monthly 1999-2022)[8]



For recovery rates, we set a baseline recovery rate of 66.4%, which is the long-term average rate of the LSTA series from 2001 to 2023),[9] as shown in **Figure 8**.

Figure 8: Recovery rates (1st lien loans), % of principal, (monthly 2001-2023)[10]



[8] Bank loan default rates from 1999 - 2022 (% of principal): *S&P, U.S. LSTA*

[9] Monthly 1st lien loan recovery rates from 2001 - 2023 (% of principal): *BofA Global Research, LCD, Moody's*

[10] Monthly 1st lien loan recovery rates from 2001 - 2023 (% of principal): *BofA Global Research, LCD, Moody's*

Although our assumptions for MM and BSL CLOs were similar for most parameters, they varied with regard to the assumed baseline default rate, which was derived as a weighted average based on the credit rating distribution of the two CLO types. We assume that rating-adjusted corporate bond default rates are approximately equal to rating-adjusted bank loan default rates. The ratings, which were sourced from S&P Global, can be seen in **Figure 9**, while the market shares can be seen in **Figure 10.**

Figure 9: Ratings distribution of CLO obligors, % (2023)[11]

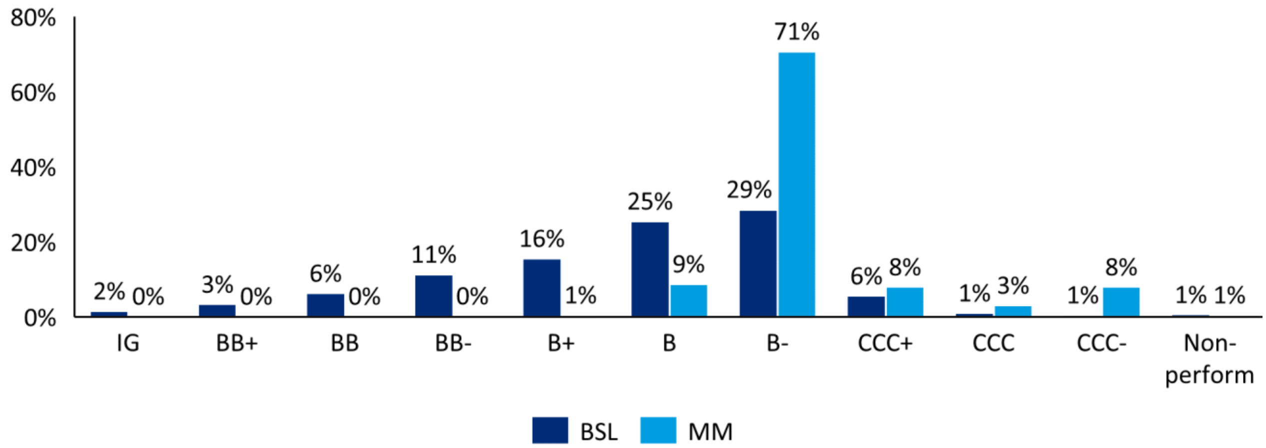
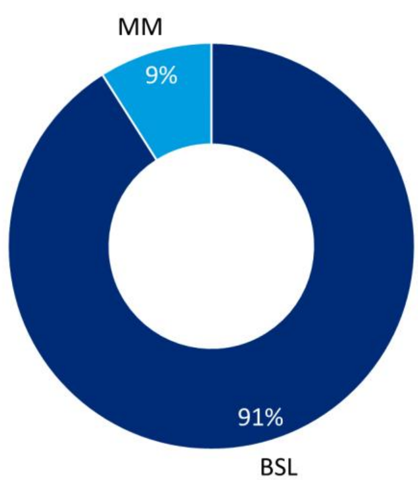


Figure 10: CLO market shares by type, % (2023)[12]



[11] Ratings distribution of CLO obligors in 2023 (%): *S&P Global Ratings, "Middle-Market CLO and Private Credit Quarterly (Q4 2023)"*

[12] MM CLO and BSL market share in 2023 (%): *S&P Global Ratings, "Middle-Market CLO and Private Credit Quarterly (Q4 2023)"*

Ultimately, this approach yielded a baseline default rate of 4.1% for MM CLOs and 2.6% for BSL CLOs. As a check on this methodology, we compared our aggregated weighted average default rate (2.80%) with that of the average default rate of the S&P LSTA index (2.75%) based on the available time series data (1999-2021). The remaining parameters were consistent across both MM and BSL CLOs.

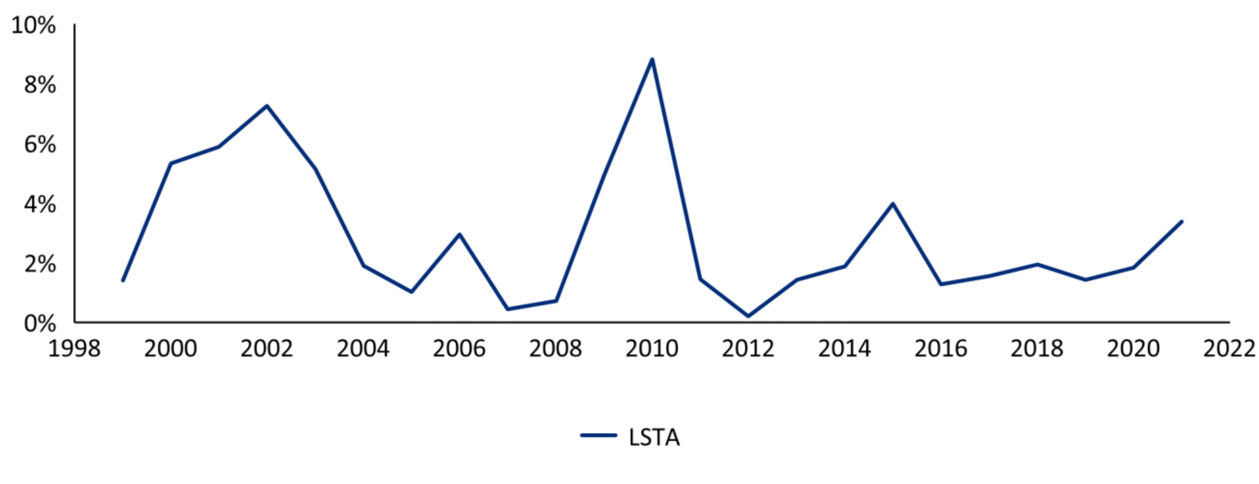
Our prepayment rate of 24.8% was derived from the average 1m annualized CPR based on the accessible historical data from BofA Global Research (2002-2023)[13]. We assumed an 18-month recovery lag across the base scenario based on an industry standard assumption; for example, Moody's[14] assumes an 18-month recovery lag in their CLO modeling. We assumed no reinvestment in all scenario; this approach is more conservative than typical market practice that assumes reinvestment at market rates. Additionally, sensitivity testing was conducted on these assumptions and is discussed later.

3.3.1.2. Mid-tail (~95th percentile) scenarios

To calibrate the default rates under the "Mid-tail" scenarios, we examined the level of defaults under two adverse credit cycles, the GFC and Dot-Com Crisis, for the S&P LSTA. While both credit events had similar levels of "excess defaults", that is the volume of defaults that occurred over the adverse portion of the credit cycle compared with the long-term average, the shape of these events differed significantly. The GFC represented a shorter, but deeper credit shock (22 months of excess defaults); the Dot-Com Crisis was a longer event (45 months of excess defaults). For both events, we applied the ratio of the default rate to the long-term average from the start of the adverse credit period (that is, when the default rate above the long-term average) until it returned to the long-term average. This path was then applied as a multiplier to the Base default rates for both BSL and MM to match the shape and scale of the two stress scenarios. This approach also allowed us to assess the sensitivity of our results to the shape of shock (short and deep vs. long and shallower).

Figure 11 below shows the historical default rate for the LSTA.

Figure 11: Bank loan default rates, % (monthly 1999-2021)[15]



[13] 1m Annualized CPR from 2002 - 2023: *BofA Global Research, LCD, Moody's*

[14] *Moody's Investors Service, "Moody's Global Approach to Rating Collateralized Loan Obligations" (2021)*

[15] Monthly bank loan default rates from 1999 - 2021 (%): *S&P, U.S. LSTA*

We calibrated recovery rates by using the average recovery rate throughout the stress cycle that followed the Dot-Com Crisis (61.1%) and GFC (58.0%), respectively, then reverting to the long-term average value (66.4%) in the periods that followed the stress. To calibrate prepayment rates, we calculated the average 1m annualized CPR for the duration of the stress (defined as periods in which the prepayment rate was less than the long-term average) for the Dot-Com Crisis and GFC, respectively. This approach yielded a prepayment rate of 18.4% for Dot-Com and 14.0% for GFC. We applied those prepayment rates for the duration of the stress, then reverted the rates back to the long-term average (24.8%) in the post-stress periods. Similar to the baseline scenario, we assumed an 18-month recovery lag based on the industry standard assumption and, for conservatism, no reinvestment.

3.3.1.3. Deep-tail scenario

As direct historical information is more limited for the "Deep-tail" scenario, we utilized historical performance data of corporate bonds during the Great Depression as a proxy for the relative losses accumulated during the modeled stress period.

To calibrate our default rates, we examined the experience for corporate bonds during the Great Depression and quantified the increase in default rates relative to the long-term average default rates. This default rate path (defined as percentage increase over the long-term average) was then applied to the baseline defaults for CLOs.

We determined stress recovery rates (55.9%) based on the lowest two-year average recovery rates within the available data range (which corresponds to June 2019 – June 2021[16]) and applied this value for a ten-year period (to match the duration of the Great Depression default curve) before reverting to the long-term average.

To calibrate our prepayment rates, we used the lowest two-year average CLO 1m Annualized CPR rate data (which corresponds to September 2007 – September 2009[17]) and applied this value (10.0%) for the ten-year stress period before reverting to the long-term average (24.8%). Similar to the baseline assumption, we assumed an 18-month recovery lag based on the industry standard assumption and, to be conservative, no reinvestment.

[16] Recovery rates from June 2019 - June 2021: *BofA Global Research, LCD, Moody's*

[17] CLO 1m annualized CPR rate from September 2007 - September 2009: *BofA Global Research, LCD, Moody's*

Figure 12: Broadly syndicated CLO annualized CDR curves, %

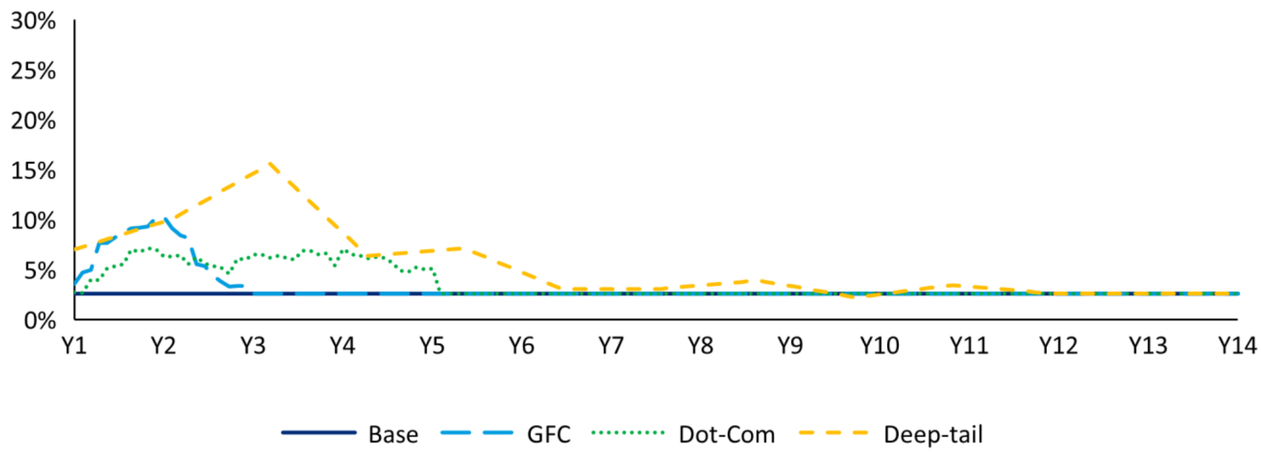
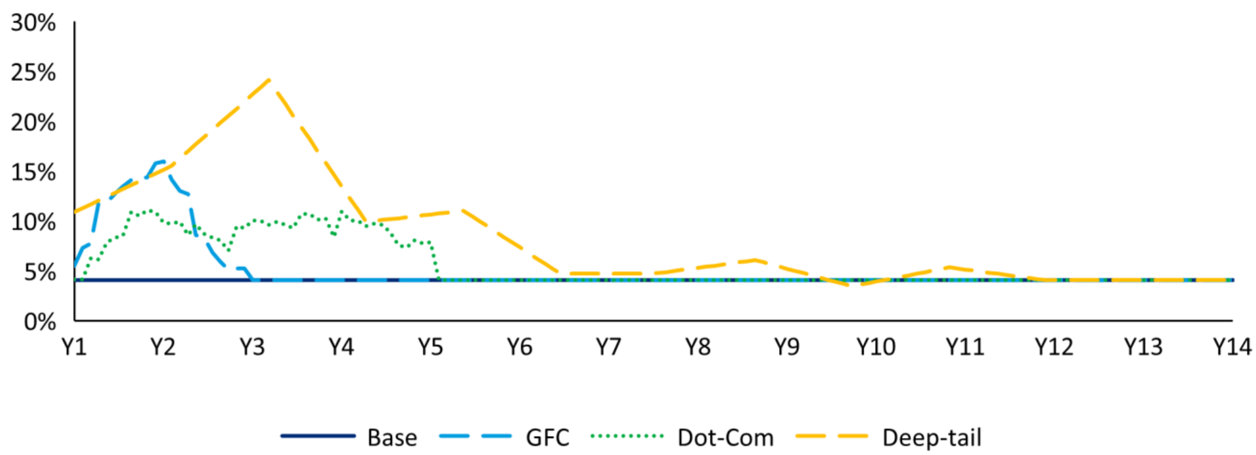


Figure 13: Middle-market CLO annualized CDR curves, %



3.3.2. Prime and subprime auto loan ABS

To calibrate scenario-level parameters for auto loan ABS, we followed a similar methodology as was followed for CLOs. Parameters were calibrated separately for prime and subprime auto loan ABS. We relied primarily on historical data on prime and subprime auto loan performance from Fitch Ratings; selected as it provided the longest time series from a reputable source.

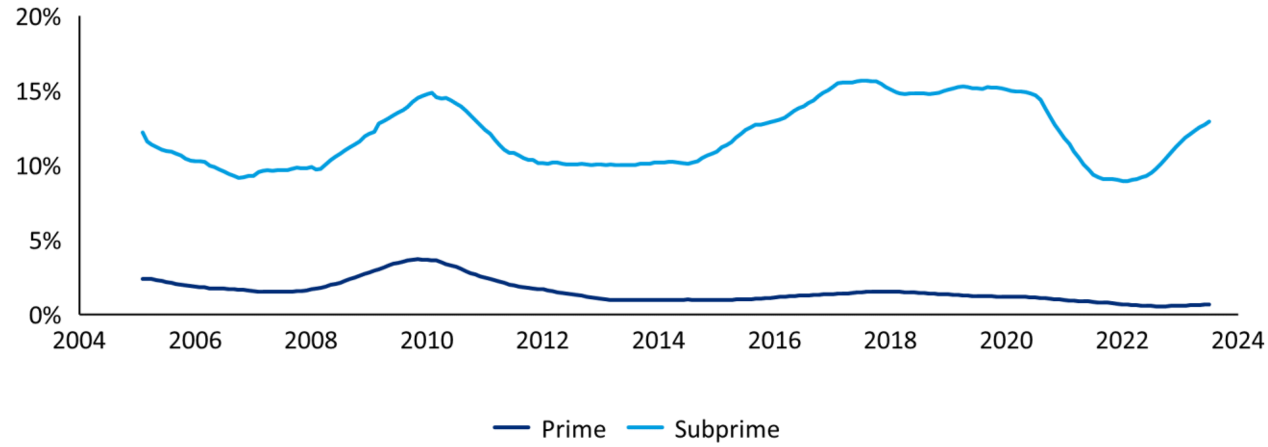
Table 3: Prime auto loan ABS scenario parameters

Parameter	Base	Mid-tail	GFC	Deep-tail
Peak default rate	1.6%	3.2%	4.4%	6.8%
Excess defaults	N/A	7%	5%	30%
Severity	41%	52%	52%	54%
Delinquency rate	0.4%	0.6%	0.6%	0.6%
Prepayment rate	1.5%	1.5%	1.5%	1.5%
Recovery lag	6 months	6 months	6 months	6 months

Table 4: Subprime auto ABS scenario parameters

Parameter	Base	Mid-tail	GFC	Deep-tail
Peak default rate	12%	16%	19%	41%
Excess defaults	N/A	14%	4%	27%
Severity	55%	61%	61%	62%
Prepayment rate	1%	1%	1%	1%
Recovery lag	6 months	6 months	6 months	6 months

Figure 14: Auto loan TTM annualized default rate, % (2005-2023)[18]



3.3.2.1. Base scenario

Our base scenario was constructed using the long-term average default rate and severity for prime and subprime for data from Fitch Ratings. Base prime delinquency rates were also determined by taking the average prime delinquency rate across the entire time series (from 2004 - 2023). Base prepayment rates were assumed based on deal-level data[19] and held constant across scenarios. Recovery lag was assumed based on rating agency auto loan ABS stress testing methodology[20] and held constant across scenarios.

3.3.2.2. Mid-tail (~95th percentile) scenarios

To calibrate the default rates under the "Mid-tail" scenarios, we examined three events (i) the GFC, during which both prime (2007-2011) and subprime (2008-2010) auto experienced above-average default rates, (ii) for subprime, heightened losses in 2015 - 2020, and (iii) as prime loans did not experience elevated losses during that period, a hypothetical event calibrated to the Dot-Com bubble, using scaled corporate bond default rates during that period (1998-2003) as a proxy to estimate prime auto loan default rates.[21]

For the GFC scenario, behavior of the modeling parameters for both prime and subprime auto loans were based on observed, historical experience during the GFC. The default rate curves for prime and subprime auto loans, as well as the severity curves for prime and subprime auto were used in Intex to simulate the GFC stress. For prime auto loan ABS, stressed delinquency rates were assumed to be the average delinquency rate during the GFC. Delinquency rates were not used as a parameter for subprime auto loan ABS due to limitations in Intex.

[18] Derived based on ANL and Recovery Rate data from Fitch Ratings

[19] Auto loan ABS benchmarking: *S&P Research*

[20] Auto loan ABS benchmarking: *S&P Research*

[21] Annual U.S. corporate bond default rates from 1920-2021 (%): *Moody's Investors Service, "Corporate Default and Recovery Rates" (2021)*

Reliable historical data on auto loan performance was not available for the Dot-Com period as it was for CLO collateral. It was still desirable to measure the impact of a more attenuated, but longer, macroeconomic stress event. We designed a longer stress event for auto but the parameters for this event had to be estimated differently than for CLOs. For prime auto loan ABS, corporate bond default rates were scaled based on the ratio of default rates between two series during the GFC, a period during which both series had default rate data. This scaled default rate data was then used to estimate auto loan default rates during the Dot-Com bubble. Subprime auto, however, suffered a second stress period in addition between 2015 and 2020. We determined it preferable to use the actual historical data in this instance. Thus, the default rates from 2015-2020 were used as the default rates for the subprime auto loan ABS Mid-tail stress scenario. We term this scenario the “Mid-tail” scenario to avoid confusion with the historical Dot-Com scenario used for CLOs. Severity, prepayment, prime delinquency, and recovery lag each remained identical to their GFC calibrations, outlined above.

Note the because the average subprime auto loan default rate is relatively high (12%), the historical data shows that the GFC and 2015-2020 stress did not cause as extreme a spike in default rates relative to the historical average, as depicted in **Figure 16**, as is observed for prime auto loans. For comprehensiveness, the deep-tail scenario is more severe in terms of peak default rate and excess defaults than the two historical mid-tail scenarios.

3.3.2.3. Deep-tail scenario

Calibration of default rate curves for the Deep-tail stress followed a similar approach to that for CLOs. Corporate bond default rates during the Great Depression (1931-1940) were used as a proxy for the default rates of auto loans during a Great Depression-like economic event. As before, these default rates were scaled based on the ratio between the corporate bond and auto loan default rates during the shared GFC period. Deep-tail severity was estimated using the worst two-year average severity during the time series. Prime delinquency, prepayment, and recovery lag remained identical to their GFC calibrations.

Figure 15: Prime auto loan ABS annualized CDR curves, %

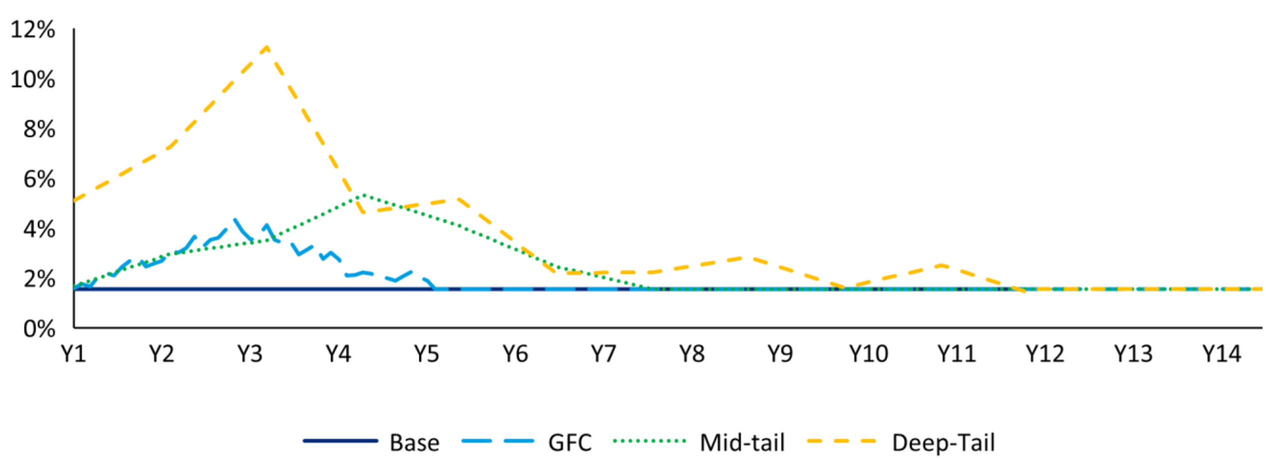
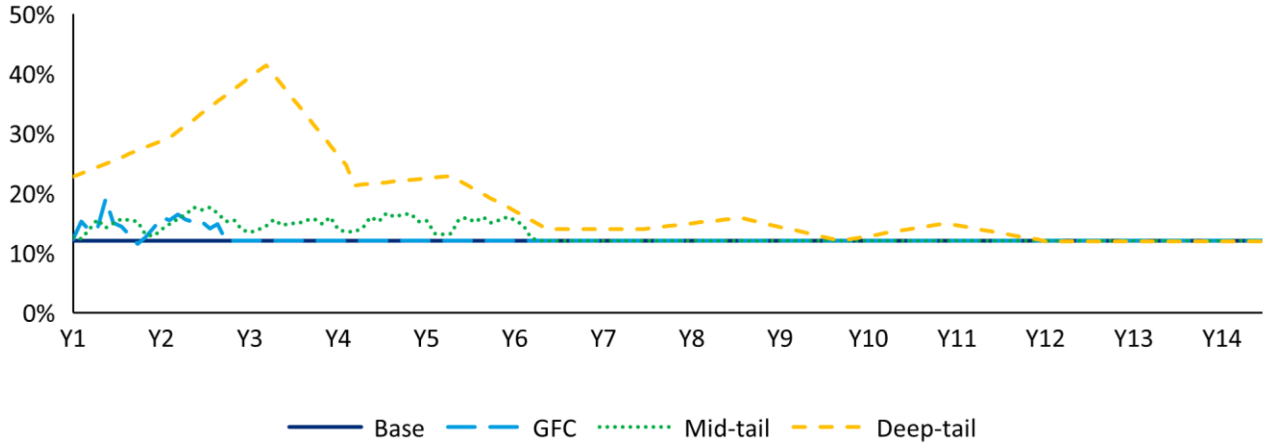


Figure 16: Subprime auto loan ABS annualized CDR curves, %



3.3.3. Student loan ABS

Table 5 shows the calibration of scenario-specific modeling parameters for private student loans. For student loans, we evaluated only a single "mid-tail" scenarios, that was calibrated based on the GFC.

Table 5: Student loan ABS scenario parameters

Parameter	Base	Mid-tail	Deep-tail
Default rate	10%	22%	22%
Excess defaults	N/A	10%	30%
Severity	69%	78%	78%
Deferment	5.8%	7.7%	7.7%
Forbearance	2.8%	4.5%	12.6%
Recovery lag	12 months	12 months	12 months

3.3.3.1. Base scenario

Analysis of student loan ABS presented challenges from a data adequacy perspective. We reviewed multiple potential sources of historical default rate data including, but not limited to, Intex, Fitch Ratings, and the National Center for Education Statistics (NCES), a federal agency. Each source captured a different universe of loans and definition of default rate that results in differences in the historical average default rates. Table 6 provides an overview of each potential source and its implied average default rates.

Table 6: Annualized student loan default rates by source

Source	Scope	Time span	Average annualized default rate
Intex	Private student loans	2008-2023	9.6%
Fitch	Private student loans	2015-2023	8.5%
NCES	Federal student loans	2011-2018	4.4%[22]

Ultimately, we chose to anchor our analysis on a base annualized default rate of 10%, but tested the robustness of our analysis to a base default rate of 8% or 12%. Base severity, deferment, and forbearance were assumed to be the long-term averages of each respective parameter, using the historical data available in Intex since 2008 . Recovery lag was assumed to be 12 months, with sensitivity analysis for a longer recovery lag period.

3.3.3.2. ~95th percentile scenario

The limited historical data availability for private student loans also affects the construction of the 95th percentile scenario. Ultimately, we took the approach of isolating the impact of the GFC on default rates by observing that the onset of the GFC resulted in a 47-month spike in default rates observed in the Intex data. We then applied the resultant excess defaults to our base default rate scenario. Severity, deferment, and forbearance were estimated by taking the averages of these parameters during the GFC; for each parameter, the stress period was defined as that period for which it exceeded its long-term average. Recovery lag was, as in the base scenario, assumed to be 12 months.

3.3.3.3. Deep-tail scenario

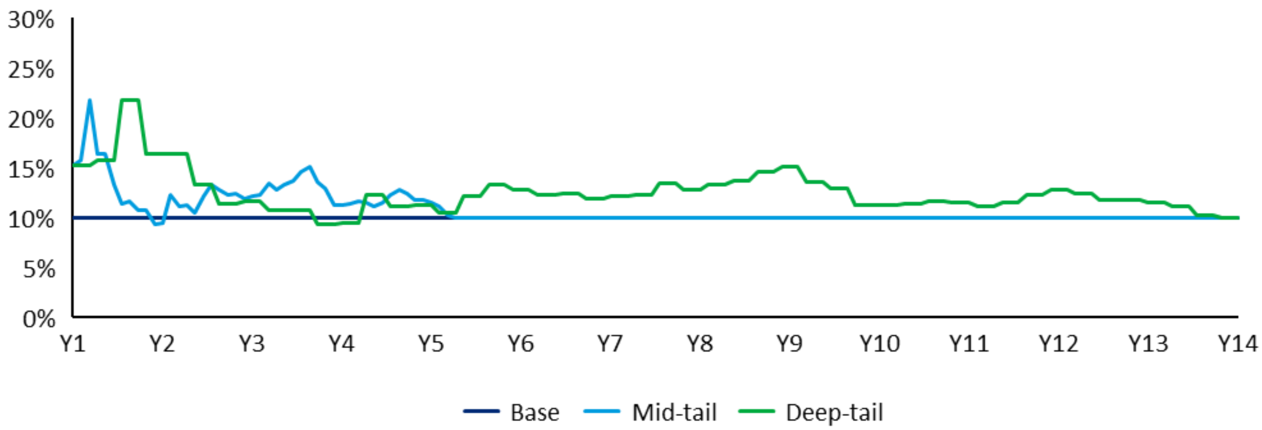
The Deep-tail scenario did not follow a similar approach to CLOs and auto loans, as corporate bonds were determined to be an insufficient analog to the performance of student loans. Student loan default and loss trajectories are not expected to follow corporate bonds, as the exposure is to narrow portions of the employment rate, interest rates, and college costs, all of which have weak correlation to corporate strains, making the latter a poor proxy. Instead, we assumed the same default rate curve as was used in our ~95th percentile stress scenario extended in duration by a factor of three, resulting in a 141-month long period of elevated defaults. Severity and deferment remained the same between the ~95th percentile scenario and the

[22] NCES measures 3-year default rates by dividing borrowers in default over a three-year period by total population of a given three-year cohort. Annualized default rate estimated by dividing NCES figure by 2.5. Sample only includes federal student loans, while Intex and Fitch series include only private student loans.

Deep-tail scenario. Forbearance was assumed to be 12.6% for the full 141-month period, the value achieved during the 2020 COVID-19 period, and the highest value recorded in our historical data series.

Figure 17 shows annualized default rate curves for 10% base default rate scenarios.

Figure 17: Student loan 10% base default rate annualized CDR curves, % default



3.4. Output Metrics

Our analysis seeks to examine the potential for losses on residual tranches in adverse scenarios. As identified as part of our guiding principles, we seek to measure losses in a manner consistent with the treatment of these assets on an insurer's statutory balance sheet.

This point itself has been in flux and is subject to different interpretations within the industry: historically, residual tranches had been held at the lower of cost of fair value[23]; more recently, this treatment has shifted to the lower of amortized cost or fair value[24]; in addition, current proposals recommend the lesser of book-adjusted carrying value or fair value. Under each of these methods, the reported value of an asset will reflect not only its fair value at the time, but the market conditions at its acquisition.

For the purposes of this analysis, we focus on the decline in fair value of an asset under the stress scenario. In an adverse stress scenario, the fair value is expected to decline below other metrics, which are less responsive to market conditions, and be the binding constraint ("lower of"). Considering only the decline in fair value, rather than attempting to fully align with the accounting treatment, is conservative as it may overstate the potential for losses under certain conditions:

- If fair value is lower than amortized cost prior to applying a stress, then considering the decline in fair value will accurately capture the loss on an insurer's balance sheet
- If fair value is greater than amortized cost prior to applying a stress, then considering the decline in fair value will overstate the potential loss on an insurer's balance sheet (by an amount equal to the starting difference between fair value and amortized cost).

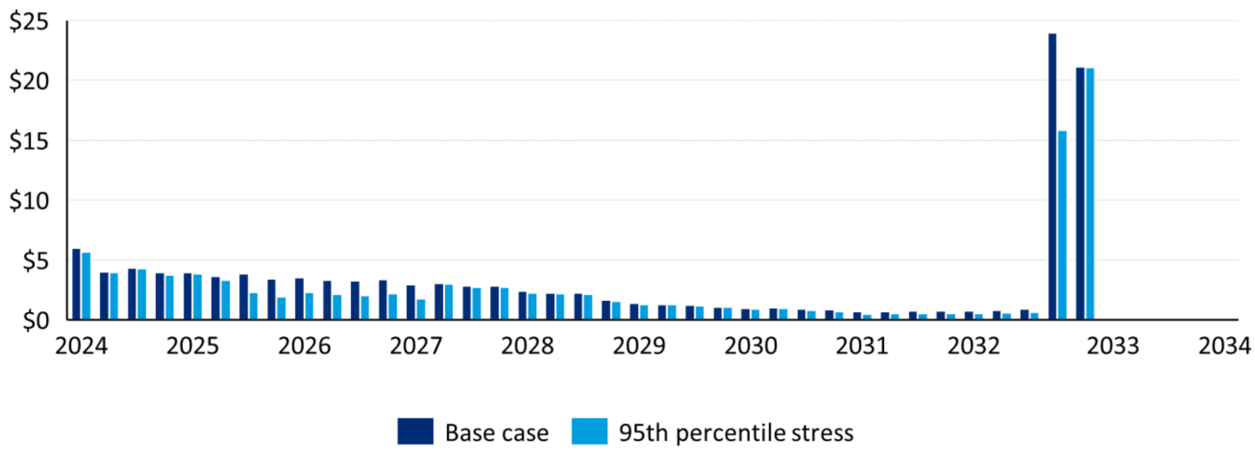
[23] SSAP No. 43R 2021-15

[24] SSAP No. 21R 12-1-23

We define 'fair value' as the net present value of the cash flows to the residual tranche at a 12% discount rate. This definition is consistent with the industry approach to valuing these types of assets (discounted cash flows) and represents a typical target return for equity-like assets. The robustness of our results relative to this parameter is evaluated in the sensitivity testing in Appendix A.3. A constant discount rate is applied in both the base and stress scenarios to isolate the impact of credit default risk from interest rate or liquidity risk.

The initial output of our modelling is a cash flow profile for each asset by scenario. **Figure 18** provides an illustrative example this output.

Figure 18: Illustrative deal level cash flow forecast, $M



4. Results

4.1. Introduction

To understand the underlying risk in residual equity tranches, **Table 8** - **Table 15** illustrate the decline in NPV using a constant discount rate of 12% across all modeled assets across our scenarios. We consider two approaches to aggregate the losses across the modeled set of assets:

- **Simple average losses:** this metric provides the simple average of losses (measured as the decline in NPV at a constant discount rate relative to the base scenario) across all modeled assets. This metric places equal weight on all assets.
- **Portfolio average losses:** this metric considers the aggregate losses on the set of modeled assets on a NPV basis; effectively, it weighs assets based on their initial fair value and illustrates the losses that an insurer would have faced if it owned that portfolio of assets.

4.2. Summary

Table 7 provides the portfolio average losses in each of the stress scenarios:

Table 7: Portfolio average losses for all modeled assets across stress scenarios

Scenario Severity	Scenario	CLOs (BSL)	CLOs (MM)	Student loans	Subprime auto loans	Prime auto loans
95th percentile	Dot-Com	-45%	-27%	-	-	-
	GFC	-42%	-25%	-	-17%	-13%
	Mid-tail	-	-	-16%	-	-
	Long Mid-tail	-	-	-	-22%	-14%
99th percentile	Deep-tail	-72%	-55%	-20%	-74%	-26%

These results indicate:

- Residual tranches for MM CLOs consistently perform better than BSL ones across our scenarios.
- Residual tranches for prime auto loans ABS consistently perform better than those backed by subprime auto loans across our scenarios.

4.3. Results by asset class

The following sections provide additional information on the results for each type of residual tranche: CLOs, auto loans, and student loans.

4.3.1. CLOs

Table 8 provides the average losses for residual tranches of CLO in each of the stress scenarios:

Table 8: CLO summary statistics

Scenario Severity	Scenario	CLO type	Simple average losses	Portfolio average losses
95th percentile	Dot-Com	BSL	-48%	-45%
		MM	-34%	-27%
	GFC[25]	BSL	-46%	-42%
		MM	-32%	-25%
99th percentile	Deep-tail	BSL	-74%	-72%
		MM	-64%	-55%

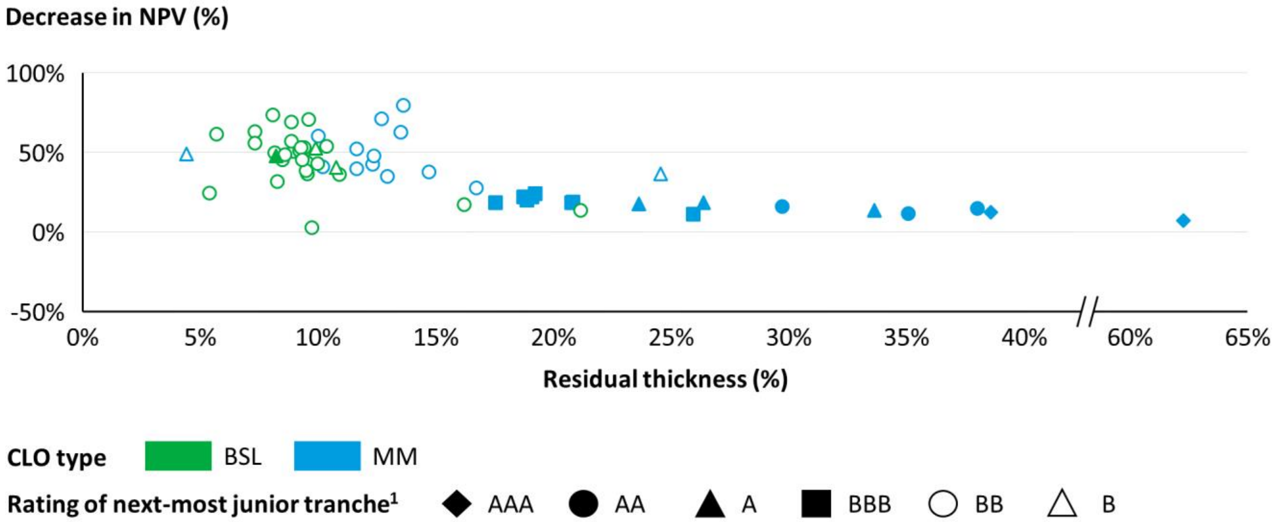
In addition, we considered the losses at the deal-level to understand the characteristics that affect the potential losses on residuals tranches. **Figure 19** illustrates losses by residual thickness in our GFC scenario. These results indicate:

- Residual tranches for MM CLOs consistently perform better than BSLs ones across our scenarios.
- CLO equity tranches with thicker residuals perform better than those with thinner residuals.
- Higher next-most junior rated CLO tranches are correlated with thicker residuals and perform better than lower rated tranches.

As shown below in **Figure 19**, residual thickness is a significant driver of stress scenario impact. CLO residual equity tranches with thicker residuals perform noticeably better than thinner residual tranches (average decrease in NPV of 49.1% when residual thickness is less than 15% vs. 18.3% when residual thickness is greater or equal to 15%). This result is consistent across our Dot-Com and Deep-tail stress scenarios as shown in **Figure** 24 and **Figure 25** in the Appendix.

[25] While credit experience was calibrated to GFC, the modeled losses differ from observed performance of CLO residual tranches during the GFC. These differences reflect several, offsetting factors, including changes to the structures of CLOs since the GFC (CLO 1.0 vs. 2.0 vs. 3.0) and the modeled assumption of no reinvestment (vs. market practices), and differences in the funding structure.

Figure 19: Losses by CLO residual thickness – Mid-tail (GFC) scenario, %



To test the robustness of our assumptions, we conducted select sensitivity testing of key parameters and assumptions such as the discount rate, recovery lag, and the prepayment rate. Details of our sensitivity testing can be seen in the Appendix. In addition, we evaluated the effect of employing the same parameters and assumptions adopted by the NAIC in its ongoing efforts around CLOs, which can be seen in **Table 9** below. Use of the NAIC assumptions had minimal impact on the simple average losses and NPV within our GFC scenario (producing a simple average loss of -45.1% vs. -45.9% for BSL and -32.9% vs. -31.6% for MM). The NAIC assumptions were applied to both the base and stress scenarios and the minimal impact reflects an offset between that reinvestment and prepayment assumptions and the faster recovery period.

Table 9: NAIC CLO assumptions

Asset Class	Assumption	NAIC assumption
CLOs (MM and BSLs)	Prepayment rates	0.0%
	Recovery lag	6 months
	Reinvestment period	No post-reinvestment period reinvestment Reinvestment collateral is purchased at par

Although it differs from how these assets are held on the balance sheet, some stakeholders may look at a cash flow coverage metric. This metric compares the total, undiscounted cash flows in a scenario to the base scenario fair value and is shown for BSL CLOs and MM CLOs in **Table 10** – **Table 11**, respectively, below.

Table 10: BSL CLO total coverage of cash flows relative to initial fair value[26]

	Mid-tail (~95th percentile)			
	Base	Dot-Com	GFC	Deep-tail
Deal-level average	1.7x	0.8x	0.9x	0.3x
Portfolio average	1.7x	0.9x	1.0x	0.3x

Table 11: MM CLO total coverage of cash flows relative to initial fair value[26]

	Mid-tail (~95th percentile)			
	Base	Dot-Com	GFC	Deep-tail
Deal-level average	1.7x	1.1x	1.2x	0.5x
Portfolio average	1.6x	1.2x	1.2x	0.7x

4.3.2. Auto loans

Table 12 provides the average loss for residual tranches of auto loans in each of the stress scenarios:

Table 12: Auto loan summary statistics

Scenario Severity	Scenario	Auto loan type	Simple average losses	Portfolio average losses
95th percentile	GFC	Prime	-13%	-13%
		Subprime	-18%	-17%
	Long Mid-tail	Prime	-14%	-14%
		Subprime	-22%	-22%
99th percentile	Deep-tail	Prime	-27%	-26%
		Subprime	-67%	-74%

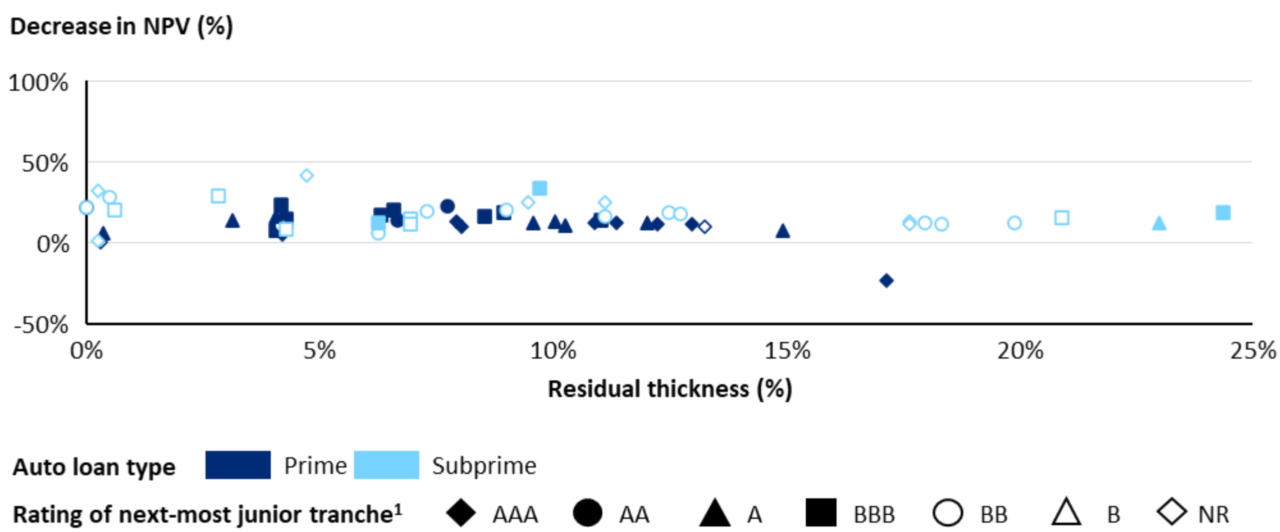
[26] Calculated by dividing total cash flow for each scenario by the base scenario fair value (base scenario cash flows discounted using a 12% discount rate)

In addition, we considered the losses at the deal-level to understand the characteristics that affect the potential losses on residual tranches. **Figure 20** illustrates losses by residual thickness in our GFC scenario. These results indicate:

- Residual tranches for prime auto loans ABS consistently perform better than those backed by subprime across our scenarios.
- Residual thickness is not as significant of a driver of stress scenario impact for auto loans as it is for CLOs.
- Higher next-most junior rated auto loan tranches perform on par with lower rated tranches.

As shown below in **Figure 20**, auto loan equity tranches with thicker residuals perform on par with those with thinner residuals in our GFC stress scenario. This result is consistent in our long Mid-tail stress scenario as shown in **Figure 26** in the Appendix. However, in our Deep-tail stress scenario, subprime auto loans with thicker residuals perform worse while prime auto loans with thicker residuals perform better as shown in **Figure 27** in the Appendix.

Figure 20: Losses by auto loan residual thickness – Mid-tail (GFC) scenario, %[27]



Although it differs from how these assets are held on the balance sheet, some stakeholders may look at a cash flow coverage metric. This metric compares the total, undiscounted cash flows in a scenario to the base scenario fair value[28] and is shown for prime and subprime auto loan in **Table 13** – **Table 14**, respectively.

[27] As shown in Figure 20, one deal experienced better performance during stress scenarios due to unique structural considerations. This deal was removed from the aggregate metrics due to outsized impacts to the portfolio and simple averages. Inclusion of this deal in portfolio aggregation would reduce losses to 6% (from 13%) under the GFC scenario and to 22% (from 26%) under the Deep-tail scenario.

[28] Calculated by dividing total cash flow for each scenario by the base scenario fair value (base scenario cash flows discounted using a 12% discount rate)

Table 13: Prime auto loan total coverage of cash flows relative to initial fair value

	Mid-tail (~95th percentile)			
	Base	Long Mid-tail	GFC	Deep-tail
Deal-level average	1.3x	1.1x	1.1x	0.9x
Portfolio average	1.3x	1.1x	1.1x	1.0x

Table 14: Subprime auto loan total coverage of cash flows relative to initial fair value

	Mid-tail (~95th percentile)			
	Base	Long Mid-tail	GFC	Deep-tail
Deal-level average	1.2x	0.9x	1.0x	0.3x
Portfolio average	1.2x	1.0x	1.0x	0.3x

To test the robustness of our assumptions, we conducted sensitivity testing of key parameters and assumptions such as the discount rate, recovery lag, base default rate, and interest rate levels. Details of our sensitivity testing can be seen in the Appendix. The results of these tests are that sensitivities had minimal impact on the simple average losses and NPV within our GFC scenario.

4.3.3. Student loans

Table 15 provides the average losses for residual tranches of student loans in each of the stress scenarios under the 10% base default rate assumption. Corresponding results for the 8% and 12% base default rate assumptions are located in the appendix.

Table 15: Student loan summary statistics

Scenario Severity	Scenario	Simple average losses	Portfolio average losses
95th percentile	Mid-tail	-31%	-16%
99th percentile	Deep-tail	-35%	-20%

In addition, we considered the losses at the deal-level to understand the characteristics that affect the potential losses on residual tranches. Figure 21 illustrates losses by residual thickness in our Mid-tail scenario. These results indicate:

- Student loan equity tranches with thinner residuals perform better than those with thicker residuals as they rely less on the principal and instead have a more consistent set of interest-based cashflows in all scenarios.
- Next-most junior rating of student loan tranches is not correlated with tranche performance.

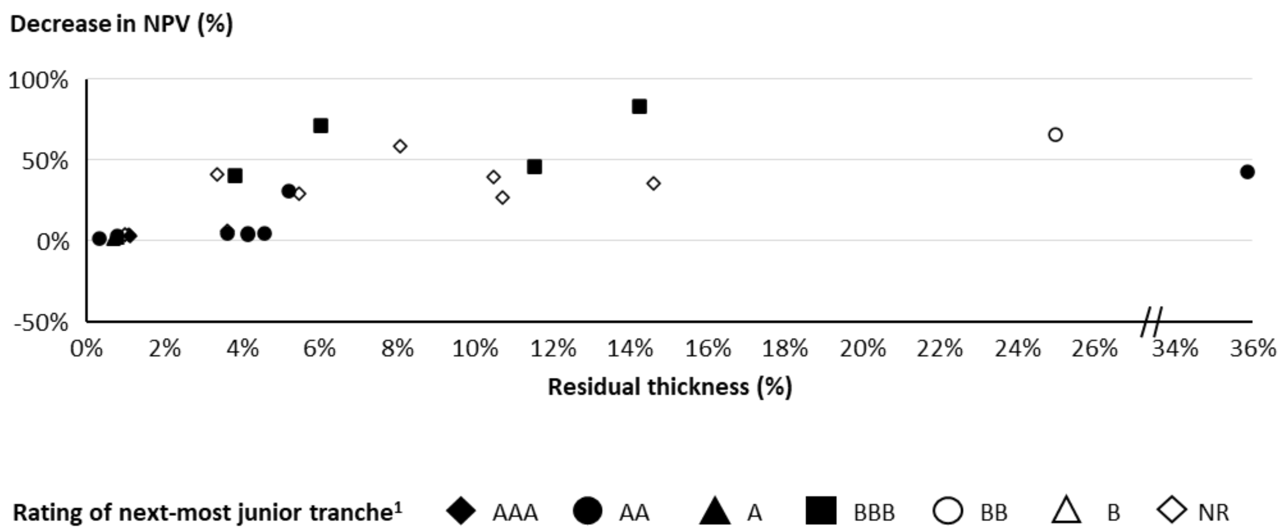
As shown below in **Figure 21**, student loan equity tranches with thinner residuals perform better than those with thicker residuals in our Mid-tail stress scenario. This result is consistent in our Deep-tail scenario as shown in **Figure 28** in the Appendix.

Although it differs from how these assets are held on the balance sheet, some stakeholders may look at a cash flow coverage metric. This metric compares the total, undiscounted cash flows in a scenario to the base scenario fair value[29] and is shown in **Table 16**.

Table 16: Student loan total coverage of cash flows relative to initial fair value

	Base	Mid-tail	Deep-tail
Deal-level average	1.6x	1.0x	1.0x
Portfolio average	1.6x	1.2x	1.2x

Figure 21: Losses by student loan residual thickness – Mid-tail scenario, %



To test the robustness of our assumptions, we chose to conduct select sensitivity testing of key parameters and assumptions such as the discount rate, recovery lag, severity, deferment rate, CRR, and forbearance. Details of our sensitivity testing can be seen in the Appendix. The results of these tests are that sensitivities had minimal impact on the simple average losses within our Mid-tail scenario.

[29] Calculated by dividing total cash flow for each scenario by the base scenario fair value (base scenario cash flows discounted using a 12% discount rate)

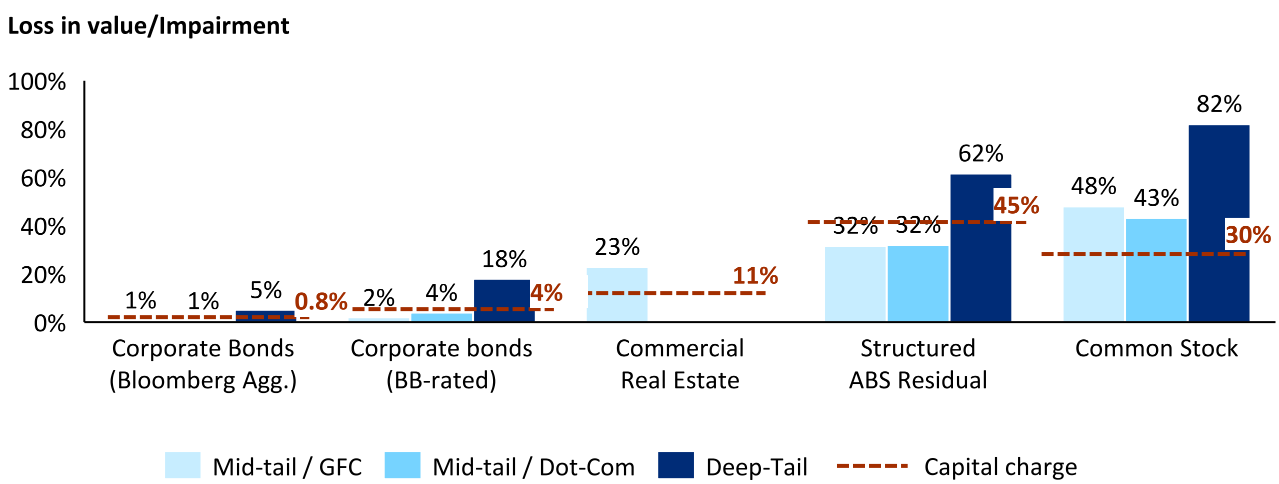
5. Conclusion

Our analysis sought to evaluate the potential for losses in the residual tranches of commonly-held types of structured assets and assess how this compares with the historical losses for other asset classes. We constructed our analysis to standardize (to the extent possible) the level of stress applied to each asset class such that an apples-to-apples, risk-based comparison could be made. We focused on two standardized points in the distribution: (i) the 95th percentile loss, as historically the NAIC has calibrated capital charges roughly to this severity and (ii) a Deep-tail event, to understand the potential for further losses in an extreme scenario.

We gauged the impact of the stress applied by measuring the decline in the Net Present Value (NPV) of the selected deals and compared them to the losses in the market value of common stock (S&P 500), due to credit impairment losses for corporate bonds (Bloomberg Aggregate Corporate Bond Index credit losses, BB rated bonds), and in the valuation of Real Estate (NCREIF index) during corresponding periods of stress.

Figure 22 below compares losses by asset class under each stress scenario. On a portfolio basis, the losses for the modeled residual tranches of structured products are lower than equities (S&P 500) under the corresponding scenarios, but higher than CRE and low-rated corporate bonds. Notably, structured ABS residuals performed better across all scenarios, when measured on a portfolio basis, than did common stock.

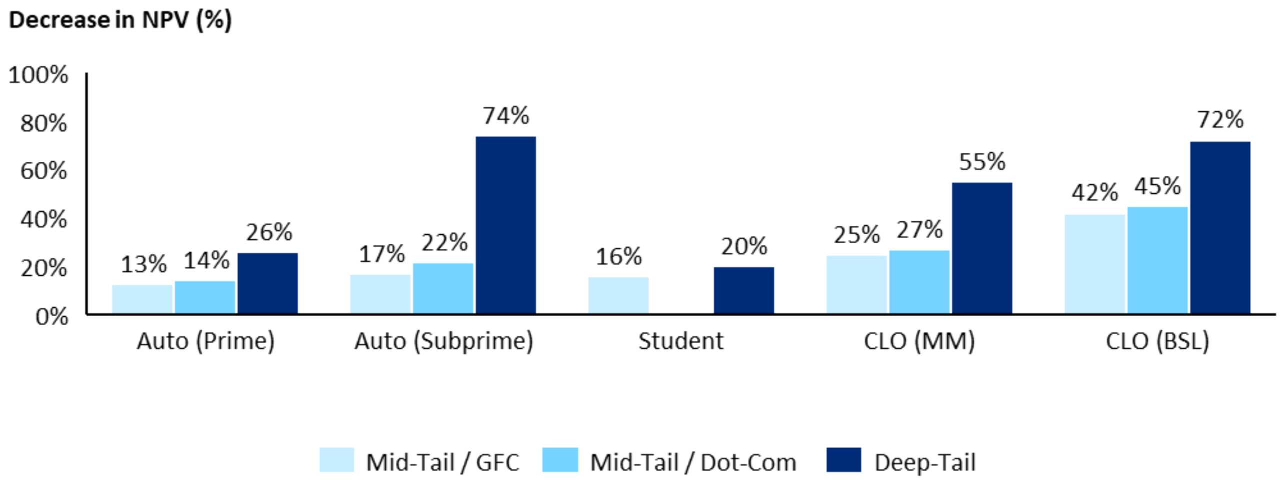
Figure 22: Capital charges compared to modeled scenario losses for selected asset classes[30]



[30] For common stock, losses are measured as the largest 2-year decline in market value for the S&P 500 during Dot-Com bubble (2000-2002) and GFC (2007-2009). For commercial real estate, losses are measured as the largest 2-year decline valuations, as measured by the NCREIF Index. For both asset classes, a 2-year window was selected to align with the calibration window for the existing NAIC capital charges. For corporate bonds, losses net of recoveries based on historical default and recovery rate data from Moody's, are shown for the full length the credit cycle including during Great Depression (1931-1940), Dot Com (1998-2003), and GFC (2008-2010). For structured ABS residuals, losses reflect the full credit cycle and the modeling approach outlined in this document; losses for modeled asset types were weighted based on the total outstanding volumes for those asset types (as-of 2021, SIFMA) and the relative volumes in the modeled sub-sectors. For student loan ABS, where only a single mid-tail scenario was evaluated, this scenario was used for aggregation purposes in both the GFC and Dot-Com scenarios. For auto loan ABS, the "long mid-tail" scenario was used for aggregation purposes in the Dot-Com scenario; this scenario was intended to capture a similar macroeconomic stress event to the Dot-Com scenario.

In addition, we consider the individual sectors and sub-sectors that were in-scope for this analysis. While significant variation is observed across sectors, reflecting differences in both the underlying collateral and the mechanics of the structures, the losses for the worse performing sector (broadly syndicated CLOs) are comparable to public equities.

Figure 23: ABS residual losses by asset class (%, decrease in NPV)[31]



[31] For student loans, only a single mid-tail scenario was evaluated.

Appendix A.

A.1. Results

Figure 24: Losses by CLO residual thickness – Mid-tail (Dot-Com) scenario, %

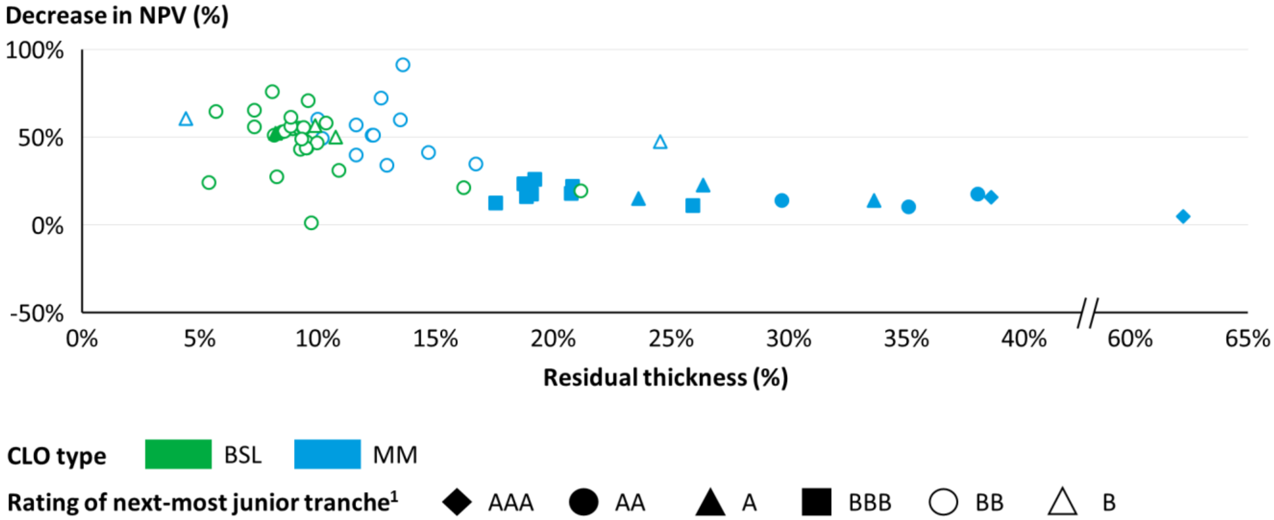


Figure 25: Losses by CLO residual thickness – Deep-tail scenario, %

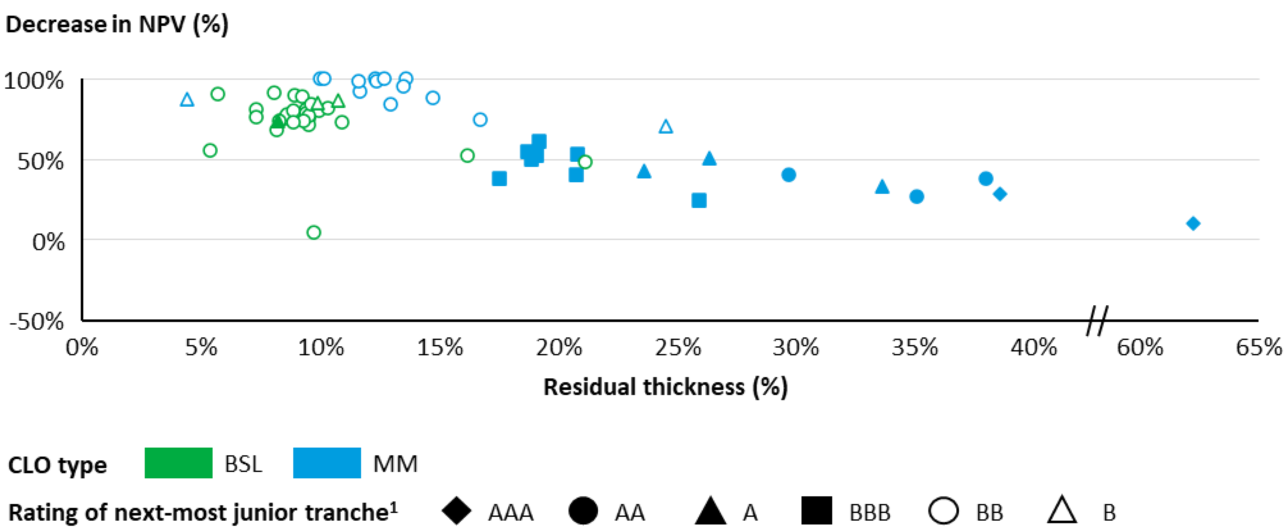


Figure 26: Losses by auto loan residual thickness – Mid-tail (Long Mid-tail) scenario, %

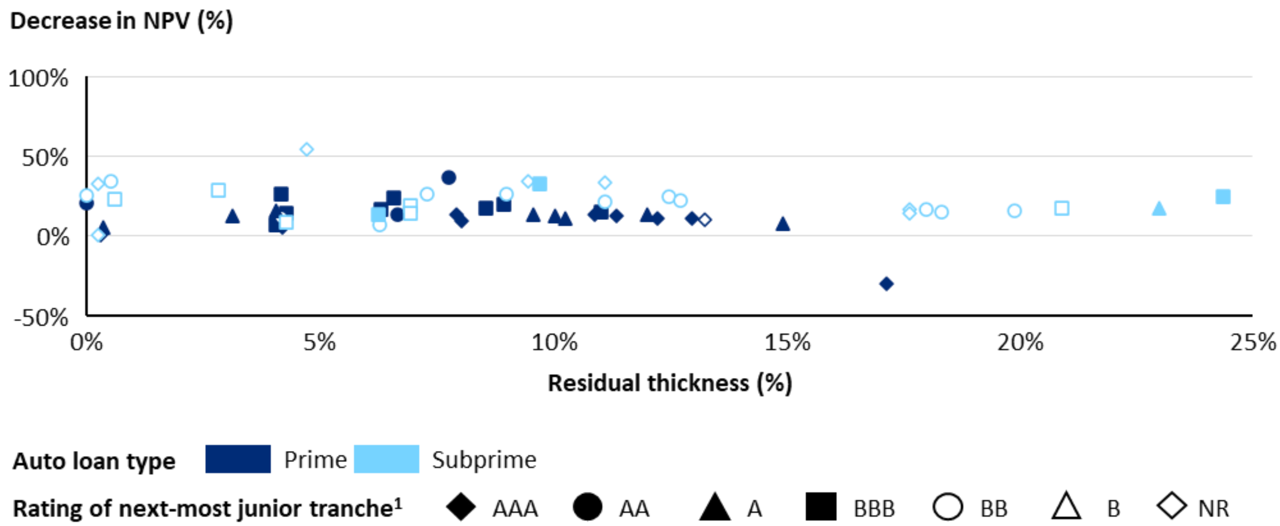


Figure 27: Losses by auto loan residual thickness – Deep-tail scenario, %

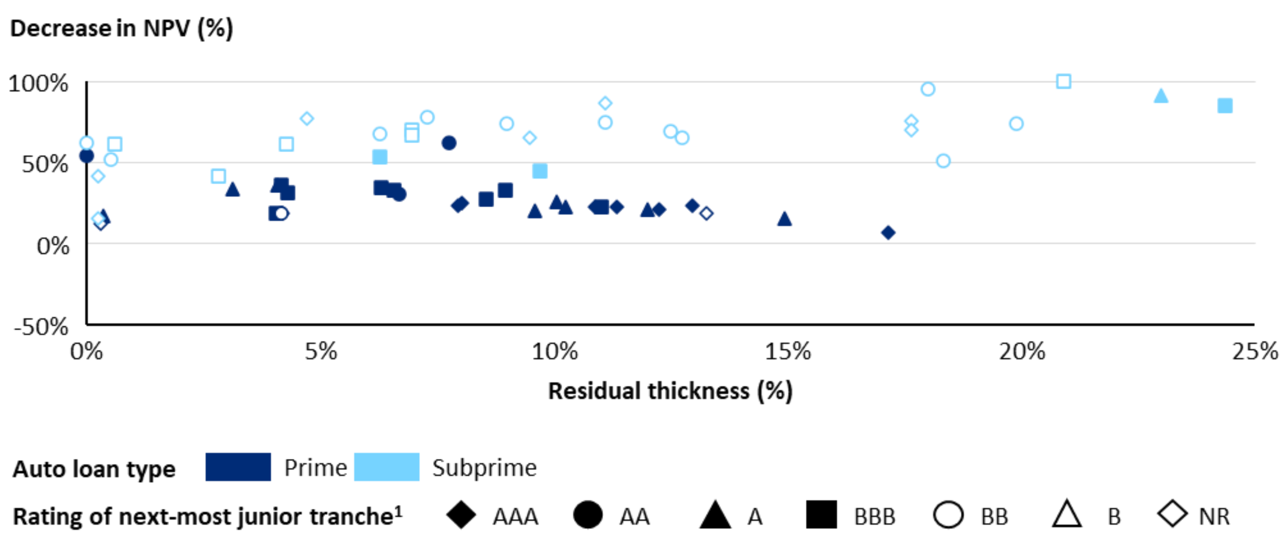
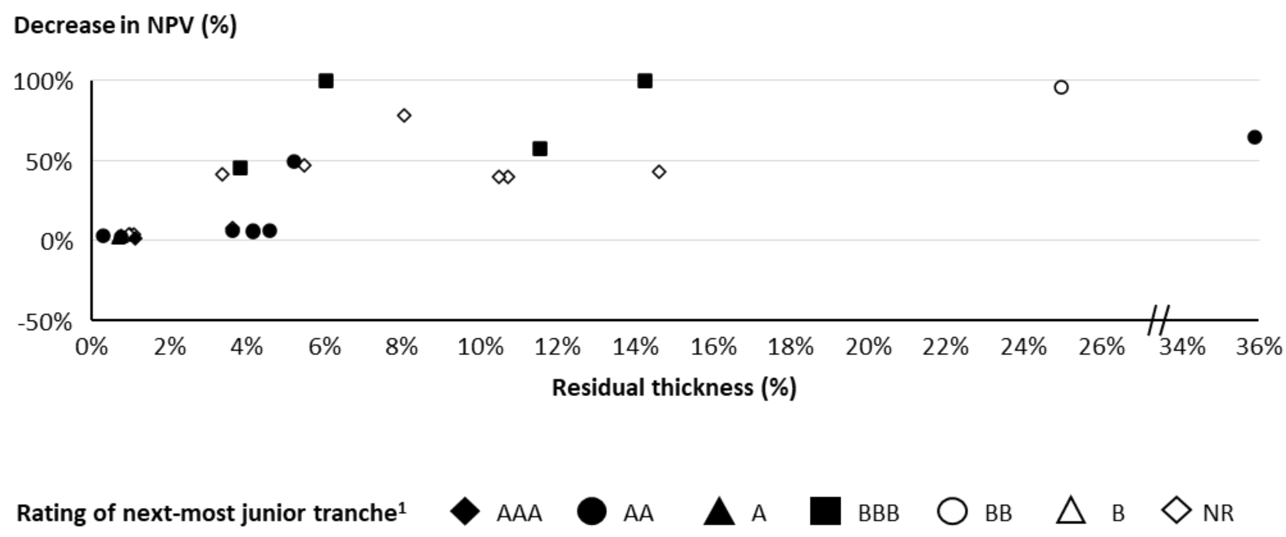


Figure 28: Losses by student loan residual thickness – Deep-tail scenario, %



A.2. Data Sources

Asset class	Sample (if known) / representative	Fields used	Time span	Provider(s)	Rationale for selection
CLOs	US LSTA 100 index leveraged loans	Default rate	1999 - 2022	S&P	Index well-used by industry, provides adequate sample of US leveraged loan market
	US first lien loans	Recovery rate	2001 – 2023	Moody's LCD Bank of America Global Research	Most comprehensive data available, compiled by BofA Global Research based on data from Moody's and LCD
Auto loans	US auto loans	Prime recovery rate Subprime recovery rate Prime ANL rate Subprime ANL rate	2004 – 2023	Fitch Ratings	Most comprehensive data available from reputable source

Asset class	Sample (if known) / representative	Fields used	Time span	Provider(s)	Rationale for selection
Student loans	US private student loans	Default rate	2008 – 2023	Intex	Most comprehensive data available FRBNY Household Debt and Credit report omitted due to use of delinquency rate over default rate NCES public student loan cohort default rates taken into consideration, but not used to calibrate scenarios Fitch Ratings private student loan default index taken into consideration, but not used to calibrate scenarios
Common stock	S&P 500 index	Share price Annual return	1928 – 2023	S&P	Used by NAIC for equity RBC framework for equities Russell 3000 omitted due to similarities of parameters to S&P 500 and shorter time span
Corporate bonds	Corporate bonds (aggregated all)	Default rate	1920-2021	Moody's	Most comprehensive data available from reputable source, well-used by industry
		Recovery rate	1982-2021	Moody's	
	Bloomberg US Corporate Bond Agg Total Return	Corporate bond price	1973-2023	Bloomberg	
Commercial Real Estate	NCREIF Property Index	Total Index Value	1978-2022	NCREIF	Used by NAIC for calibration of RBC framework for CRE FRED US Commercial Real Estate price index omitted due to greater sensitivity to market price rather than valuation, as well as due to the NAIC's use of NCREIF data for their RBC framework

A.3. Sensitivity Analysis

Details of CLO sensitivity testing in our GFC scenario can be found below:

- **Discount rate:**
  - For BSLs, a discount rate of 12% resulted in a simple average loss relative to the base scenario of -45.9% compared to -45.7% and -46.1% for discount rates of 9% and 15%, respectively.
  - For MMs, a discount rate of 12% resulted in a simple average loss relative to the base scenario of -31.6% compared to -31.1% and -32.1% for discount rates of 9% and 15%, respectively.
- **Recovery lag:**
  - For BSLs, a 6-month recovery lag resulted in a NPV 5.4% higher on average than our base 12-month assumption while a 12-month recovery lag resulted in a NPV 0.7% higher on average.
  - For MMs, a 6-month recovery lag resulted in a NPV 0.3% higher on average than our base 12-month assumption while a 12-month recovery lag resulted in a NPV 0.8% lower on average.
- **Prepayment rate:**
  - For BSLs, a consistent prepayment rate across base and GFC scenario resulted in a NPV 6.2% lower on average than when we apply scenario-specific prepayment assumptions.
  - For MMs, a consistent prepayment rate across base and GFC scenario resulted in a NPV 3.4% lower on average than when we apply scenario-specific prepayment assumptions.

Details of auto loan sensitivity testing in our GFC scenario can be found below:

- **Discount rate:**
  - For prime auto loans, a discount rate of 12% resulted in a simple average loss relative to the base scenario of -13.0% compared to -12.9% and -13.0% for discount rates of 9% and 15%, respectively.
  - For subprime auto loans, a discount rate of 12% resulted in a simple average loss relative to the base scenario of -18.2% compared to -18.5% and -17.9% for discount rates of 9% and 15%, respectively.
- **Recovery lag:**
  - For prime auto loans, a 3-month recovery lag resulted in a NPV 1.7% lower on average than our base 6-month assumption while a 9-month recovery lag resulted in a NPV 1.5% higher on average.
  - For subprime auto loans, a 3-month recovery lag resulted in a NPV 3.3% lower on average than our base 6-month assumption while a 9-month recovery lag resulted in a NPV 5.5% higher on average.
- **Base default rate:**
  - For prime auto loans, a 0.5% increase in our base default rate resulted in a NPV 0.0% lower on average while a 0.5% decrease in our base default rate resulted in a NPV 0.0% higher on average.
  - For subprime auto loans, a 1.0% increase in our base default rate resulted in a NPV 1.9% lower on average while a 1.0% decrease in our base default rate resulted in a NPV 2.0% higher on average.
- **Rate shock:**
  - For prime auto loans, applying a 50bps rate shock to forward curves resulted in a NPV 0.2% lower on average.

  - For subprime auto loans, applying a 50bps rate shock to forward curves resulted in a NPV 1.6% lower on average.

Details of student loan sensitivity testing in our Mid-tail scenario can be found below:

- **Discount rate:**
  - A discount rate of 12% resulted in a simple average loss relative to the base scenario of -31.4% compared to -31.4% and -31.5% for discount rates of 9% and 15%, respectively.
- **Recovery lag:**
  - An 18-month recovery lag resulted in a simple average loss relative to the base scenario of -25.0% compared to a simple average loss of -31.4% with our base 12-month assumption.
- **Severity:**
  - 85% severity resulted in a simple average loss relative to the base scenario of -28.5% compared to a simple average loss of -31.4% with our base 77% severity assumption.
- **Deferment rate:**
  - A 10% deferment rate resulted in a simple average loss relative to the base scenario of -29.9% compared to a simple average loss of -31.4 % with our base 8% assumption while a 12% deferment rate resulted in a simple average loss of -30.1%.
- **CRR:**
  - 15% CRR resulted in a simple average loss relative to the base scenario of -28.5% compared to a simple average loss of -31.4% with our base CRR assumptions while 25% CRR resulted in a simple average loss of -27.5%.
- **Forbearance:**
  - 10% forbearance resulted in a simple average loss relative to the base scenario of -28.6% compared to a simple average loss of -31.4% with our base forbearance assumptions while 15% forbearance resulted in a simple average loss of -25.7%.
- **Default rate:**
  - An 8% default rate resulted in a simple average loss relative to the base scenario of -25.2% compared to a simple average loss of -31.4% with our base default rate assumptions while a 12% default rate resulted in a simple average loss of -31.4%.

A.4. Deals Modeled

Table 17: Listing of MM CLO deals in random modeling sample

Deal	Vintage
Audax Senior Debt CLO 6	2021
Owl Rock CLO VII	2022
Guggenheim MM CLO 2021-4	2021
Lake Shore MM CLO V	2022
Maranon Loan Funding 2023-1	2023
Owl Rock CLO VI	2021
Woodmont 2023-12 Trust	2023
Owl Rock CLO X	2023
BCC Middle Market CLO 2023-2	2023
Fortress Credit Opportunities XXI CLO	2023
BlackRock DLF IX 2021-2 CLO	2021
MFIC Bethesda CLO 1	2023
Twin Brook CLO 2023-1	2023
Deerpath Capital CLO 2022-1	2022
Barings Middle Market CLO 2023-I	2023
Blackrock Mt Adams CLO IX	2021
Guggenheim MM CLO 2021-3	2021
Barings Private Credit Corporation CLO 2023-1	2023
Golub Capital Partners ABS Funding 2023-1	2023
ABPCI Direct Lending Fund CLO XIV	2023
Blackrock Rainier CLO VI	2021
Owl Rock CLO VIII	2022
ABPCI Direct Lending Fund CLO XVI	2023
Churchill MMSLF CLO-I	2021
Lake Shore MM CLO IV	2021
Golub Capital Partners CLO 56(M)	2021
BlackRock DLF X 2022-1 CLO	2022
Golub Capital Partners CLO 57(M)	2021
Antares CLO 2021-1	2021

Table 18: Comparison of characteristics random sample to full pool of deals: MM CLO

Statistic	Random sample	Full sample
Average deal balance	\$534M	\$489M
10th – 90th percentile	\$350M - 902M	\$304M - \$735M
Average residual thickness	20%	24%
10th – 90th percentile	10%-35%	12%-35%
2021 vintage	40%	33%
2022 vintage	20%	24%
2023 vintage	40%	43%

Table 19: Listing of BSL CLO deals in random modeling sample

Deal	Vintage
Venture 48 CLO	2023
Rockford Tower CLO 2021-1	2021
Palmer Square CLO 2023-3	2023
MidOcean Credit CLO XI	2022
Octagon Investment Partners 54	2021
Wellfleet CLO 2021-1	2021
Bain Capital Credit CLO 2023-1	2023
Sculptor CLO XXV	2021
Wellington Management CLO 1	2023
Fortress Credit BSL XX	2023
Rockford Tower Credit Funding I	2022
Milford Park CLO	2022
Dryden 90 CLO	2021
Carlyle U.S. CLO 2023-2	2023
KKR Static CLO I	2022
Sound Point CLO XXX	2021
Octagon 70 Alto	2023
Madison Park Funding LII	2021
OHA Credit Funding 12	2022
RRX 6	2021
AIMCO CLO 12	2021
Mountain View CLO XVI	2022
AGL CLO 10	2021
Ares LXVIII CLO	2023

Deal	Vintage
Carlyle U.S. CLO 2021-9	2021
Sculptor CLO XXVIII	2021
BCRED BSL CLO 2021-2	2021
Octagon 61	2023
Atlantic Avenue 2023-1	2023
Octagon Investment Partners 49	2021

Table 20:Comparison of characteristics random sample to full pool of deals: BSL CLO

Statistic	Random sample	Full sample
Average deal balance	$443M	$460M
10^{th} – 90^{th} percentile	$366M – $515M	$383M – $576M
Average residual thickness	10%	9%
10^{th} – 90^{th} percentile	7% - 11%	7% - 10%
2021 vintage	47%	44%
2022 vintage	20%	30%
2023 vintage	33%	26%

Table 21: Listing of Prime Auto ABS deals in random modeling sample

Deal	Vintage
Toyota Auto Receivables 2022-D Owner Trust	2022
Toyota Auto Receivables 2022-B Owner Trust	2022
Capital One Prime Auto Receivables Trust 2022-1	2022
World Omni Auto Receivables Trust 2022-B	2022
OCCU Auto Receivables Trust 2022-1	2022
SCCU Auto Receivables Trust 2023-1 (Space Coast Credit Union)	2023
Toyota Auto Receivables 2021-B Owner Trust	2021
SFS Auto Receivables Securitization Trust 2023-1	2023
Porsche Financial Auto Securitization Trust 2023-1	2023
World Omni Auto Receivables Trust 2022-D	2022
Lendbuzz Securitization Trust 2023-2	2023
OCCU Auto Receivables Trust 2023-1	2023
World Omni Auto Receivables Trust 2022-A	2022
World Omni Auto Receivables Trust 2021-D	2021
World Omni Auto Receivables Trust 2023-D	2023

Deal	Vintage
BVABS 2023-CAR2 aka BOF URSA VII Funding Trust I	2023
CarMax Auto Owner Trust 2021-1	2021
Hyundai Auto Receivables Trust 2022-C	2022
Ent Auto Receivables Trust 2023-1	2023
Toyota Auto Loan Extended Note Trust 2023-1	2023
Capital One Prime Auto Receivables Trust 2023-2	2023
Toyota Auto Receivables 2023-B Owner Trust	2023
Toyota Auto Receivables 2023-C Owner Trust	2023
Ally Auto Receivables Trust 2022-2	2022
Chase Auto Owner Trust 2022-A	2022
GM Financial Revolving Receivables Trust 2023-2	2023
Capital One Prime Auto Receivables Trust 2021-1	2021
Toyota Auto Receivables 2023-D Owner Trust	2023
Westlake Automobile Receivables Trust, Series 2023-P1	2023
GM Financial Consumer Automobile Receivables Trust 2022-4	2022

Table 22: Comparison of characteristics random sample to full pool of deals: Prime auto loan

Statistic	Random sample	Full sample
Average deal balance	$1.1B	$1.3B
10^{th} – 90^{th} percentile	$256M – $1.6B	$419M – $1.9B
Average residual thickness	8%	6%
10^{th} – 90^{th} percentile	3%-13%	0%-13%
2021 vintage	13%	26%
2022 vintage	37%	28%
2023 vintage	50%	46%

Table 23: Listing of Subprime Auto ABS deals in random modeling sample

Deal	Vintage
Santander Drive Auto Receivables Trust 2023-4	2023
United Auto Credit Securitization Trust 2023-1	2023
Flagship Credit Auto Trust 2021-3	2021
Research-Driven Pagaya Motor Asset Trust VI	2022
CPS Auto Receivables Trust 2023-B	2023
American Credit Acceptance Receivables Trust 2022-4	2022

Deal	Vintage
Research-Driven Pagaya Motor Asset Trust VII	2022
United Auto Credit Securitization Trust 2021-1	2021
First Investors Auto Owner Trust 2021-1	2021
AmeriCredit Automobile Receivables Trust 2021-1	2021
Tricolor Auto Securitization Trust 2022-1	2022
Lobel Automobile Receivables Trust 2023-2	2023
Westlake Automobile Receivables Trust 2023-3	2023
LAD Auto Receivables Trust 2023-2	2023
Foursight Capital Automobile Receivables Trust 2022-1	2022
Foursight Capital Automobile Receivables Trust 2021-2	2021
CPS Auto Receivables Trust 2021-A	2021
American Credit Acceptance Receivables Trust 2021-3	2021
Lendbuzz Securitization Trust 2023-1	2023
Strike Acceptance Auto Funding Trust 2023-2	2023
Flagship Credit Auto Trust 2022-4	2022
Westlake Automobile Receivables Trust 2023-2	2023
American Credit Acceptance Receivables Trust 2022-2	2022
Research-Driven Pagaya Motor Asset Trust IV	2021
GLS Auto Receivables Issuer Trust 2023-1	2023
Westlake Automobile Receivables Trust 2022-2	2022
Research-Driven Pagaya Motor Asset Trust III	2021
Arivo Acceptance Auto Loan Receivables Trust 2021-1	2021

Table 24: Comparison of characteristics random sample to full pool of deals: Subprime auto loan

Statistic	Random sample	Full sample
Average deal balance	\$506M	\$607M
$10^{th} – 90^{th}$ percentile	\$44M – \$836M	\$183M – \$1.5B
Average residual thickness	10%	11%
$10^{th} – 90^{th}$ percentile	1%-20%	1%-25%
2021 vintage	36%	33%
2022 vintage	29%	30%
2023 vintage	36%	36%

Table 25: Listing of Student Loan ABS deals in random modeling sample

Deal	Vintage
Nelnet Student Loan Trust 2023-A	2023
SMB Private Education Loan Trust 2021-A	2021
College Ave Student Loans 2021-A	2021
Nelnet Student Loan Trust 2023-PL1	2023
Commonbond Student Loan Trust 2021-A-GS	2021
College Ave Student Loans Trust 2021-5	2021
Navient Private Education Refi Loan Trust 2021-E	2021
College Ave Student Loans 2023-A	2023
Navient Private Education Refi Loan Trust 2022-B	2022
Commonbond Student Loan Trust 2021-B-GS	2021
College Ave Student Loans 2021-C	2021
Navient Private Education Refi Loan Trust 2021-F	2021
College Ave Student Loans 2021-B	2021
Nelnet Student Loan Trust 2021-A	2021
ELFI Graduate Loan Program 2021-A	2021
Navient Private Education Refi Loan Trust 2021-B	2021
College Ave Student Loans Trust 2021-3	2021
Nelnet Student Loan Trust 2021-C	2021
Navient Private Education Refi Loan Trust 2021-A	2021
Navient Private Education Loan Trust 2023-B	2023
College Ave Student Loans 2023-B	2023
Prodigy Finance CM2021-1	2021
Nelnet Student Loan Trust 2021-D	2021
Navient Private Education Refi Loan Trust 2021-G	2021
College Avenue Student Loans 2022-CLUB	2022
EDvestinU Private Education Loan Issue No. 4 Series 2022-A	2022
SMB Private Education Loan Trust 2023-A	2023
College Ave Student Loans Trust 2021-4	2021
SMB Private Education Loan Trust 2021-E	2021
Navient Private Education Refi Loan Trust 2022-A	2022

Table 26: Comparison of characteristics random sample to full pool of deals: Student loan

Statistic	Random sample	Full sample
Average deal balance	$506M	$484M
10th – 90th percentile	$81M – $1.0B	$82M – $999M
Average residual thickness	9%	-
10th – 90th percentile	1%-18%	-
2021 vintage	67%	71%
2022 vintage	13%	13%
2023 vintage	20%	16%

Table 27: Excluded deals[32]

Class	Name
MM CLO	Churchill MMSLF CLO-II
Prime auto loan ABS	Bank of America Auto Trust 2023-2
	Carvana Auto Receivables Trust 2023-P1
	Carvana Auto Receivables Trust 2023-P4
	Westlake Automobile Receivables Trust, Series 2023-P1
	Carvana Auto Receivables Trust 2023-P2
	Honda Auto Receivables 2022-1 Owner Trust
	Honda Auto Receivables 2023-4 Owner Trust
Subprime auto loan ABS	Carvana Auto Receivables Trust 2021-N4
	Juniper Receivables 2022-1
	Credit Acceptance Auto Loan Trust 2023-3
	Credit Acceptance Auto Loan Trust 2023-5
	Flagship Credit Auto Grantor Trust 2023-R
	Carvana Auto Receivables Trust 2022-N1
Student loan ABS	SMB Private Education Loan Trust 2022-A
	Brazos Education Loan Authority Series 2021-1
	SMB Private Education Loan Trust 2022-B
	Kentucky Higher Education Student Loan Corporation, Series 2021-1
	Navient Student Loan Trust 2021-3
	Higher Education Loan Authority of the State of Missouri Series 2021-2
	Higher Education Loan Authority of the State of Missouri Series 2021-3
	SoFi Professional Loan Program 2021-A

[32] No BLS CLO deals were excluded

New Mexico Educational Assistance Foundation, Series 2021-1
Towd Point Asset Trust 2021-SL1

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