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Via Electronic Submission

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Over the past two years, given the emerging importance of the asset class, the NAIC and other stakeholders have examined insurance company asset-backed security (ABS) holdings, particularly ABS residual tranches. After a significant debate and under instructions to move forward rapidly, the NAIC decided on an interim basis, by YE 2024, to increase the risk-based capital charges for ABS residual tranches from 30% to 45% on an interim basis. However, we appreciate that you and several other NAIC officials, on

[1] The Alternative Credit Council (ACC) is a global body that represents asset management firms in the private credit and direct lending space. It currently represents 250 members that manage over $1trn of private credit assets. The ACC is an af3 (t)2.[a)2eve C

several occasions, have publicly expressed an openness to interested parties providing credible data that could demonstrate whether or not a 45% residual capital charge is appropriate and, potentially, changing the interim charge to be consistent with that data. In response to these statements, we have engaged Oliver Wyman (OW) to conduct an independent analysis of the relative(r)-3.8 (e)-3.8is (r)-3.8 (e)-3.801 Tw 01 T7 (t)-4.2 (he)-3.9 ( )0A(ym)-

We believe the data presented in the OW study is persuasive that the 45% interim risk-based capital charge does not reflect the actual risk when compared to the capital charges and losses of the other assets listed in Figure 23. We also believe this additional data provides ample evidence that more diligence should be done before imposing any interim capital charge, and we suggest an implementation delay to allow further consideration of any and all data put forth by interested parties. We welcome questions and dialogue on the OW study results and look forward to receiving your feedback. If

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February 26, 2024

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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 scen-arios, tail th” (-95 percentile) and “deep-tail” stress scenarios, on a portfolio so 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 e and for each asset e aBTreTd

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.

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 [illegible] risk associated with these [illegible] support a calibration of a capital charge for u [illegible]

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.

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For each subclass of ABS, we followed the steps below in

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 meth 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, th 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. 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-

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 , while the market shares can be seen in

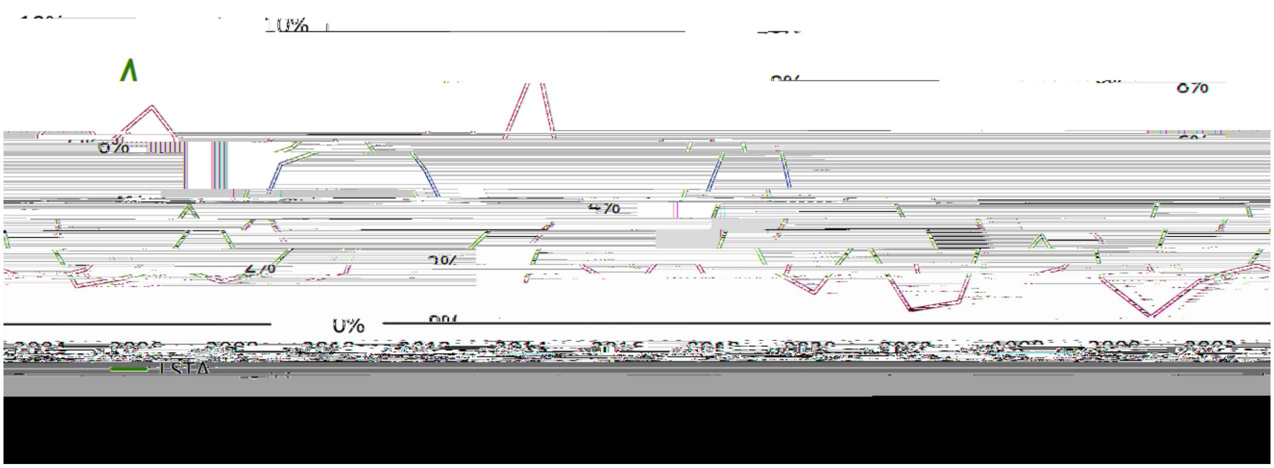
[11] Ratings distribution of CLO obligors in 2023 (%): ^ ˜ W ' o } o Z š] v P • U ^ D] o

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 b a s e s c e n a r i o b a s e d o n a n i n d u s t r y s t a n d a r d a s s u m p t i o n ; f [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.

To calibrate the default rates under the " M - t a i l " s c e n 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 o f " e x c e s s d e f a u l t s " , t h a t i s t h e v o l u m e o f d e f a u l t s t h a t 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).

below shows the historical default rate for the LSTA.



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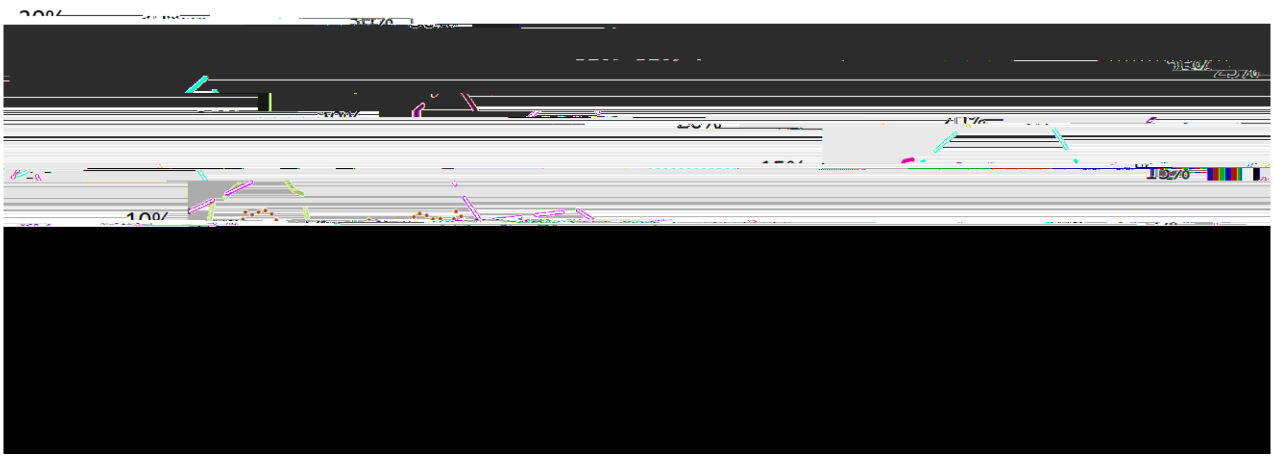
[13] 1m Annualized CPR from 2002 - 2023: } (' o } o Z • Œ Z U > U D } } Ç [•

[14] D } } Ç [• / v À • š } Œ • ^ Œ À] U ^ D } } Ç [• ' o } o ‰ ‰ Œ } Z š } (2021) š] v P } o o š Œ o] Ì > } v K o

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



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To calibrate scenario-

[redacted]

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.

To calibrate the default rates [illegible] 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 (%): D } } Ç [• /vÀ •š}Œ• ^ ŒÀ] U ^ }Œ‰}Œ š (µoš v (2021)

Table 5

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.

	Private student loans	2008-2023	9.6%	
	Private student loans	2015-2023	8.5%	
	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.

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.

We define 'value' as the net present value of the cash flows to
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. provides an illustrative example this output.

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

	Dot-Com	BSL	-48%	-45%
		MM	-34%	-27%
	GFC[25]	BSL	-46%	-42%
		MM	-32%	-25%
	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. 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 , 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 24 and 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.

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 – , respectively, below.

	Base	Dot-Com	GFC	Deep-tail
	1.7x	0.8x	0.9x	0.3x
	1.7x	0.9x	1.0x	0.3x

	Base	Dot-Com	GFC	Deep-tail
	1.7x	1.1x	1.2x	0.5x
	1.6x	1.2x	1.2x	0.7x

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

GFC	Prime	-13%	-13%
	Subprime	-18%	-17%

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-

In addition, we consider the individual sectors and sub-sectors that were in-scope for this analysis. While

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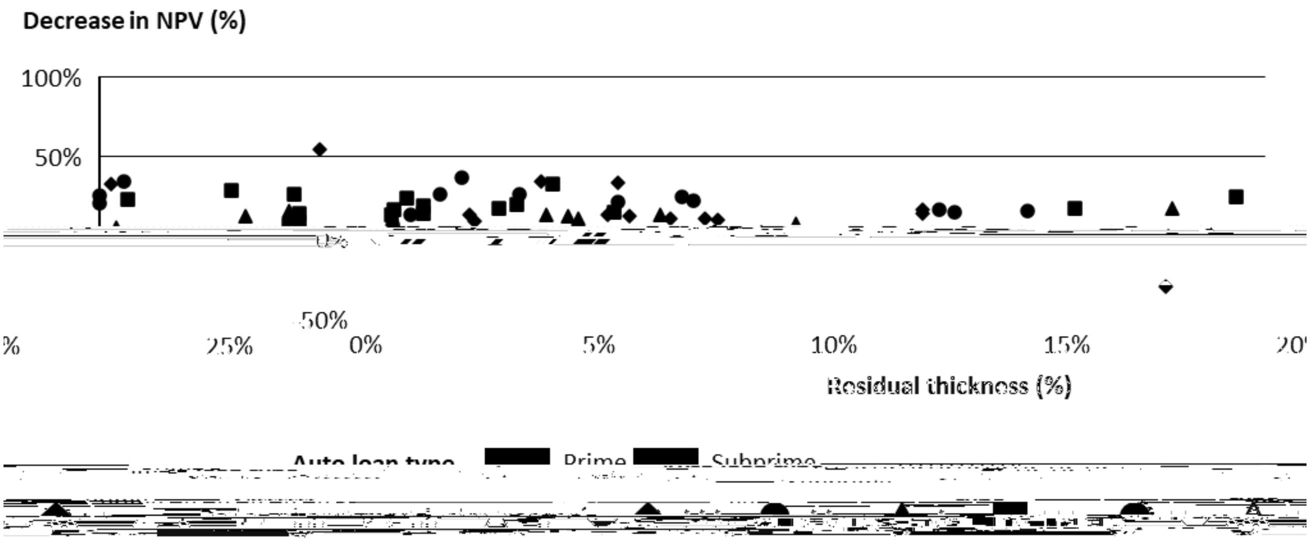
Decrease in NPV (%)
100%
50%
-50%
0%
5%
10%
15%
Residual thickness (%)
Auto loan type
Prime
Subprime

t

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 loanacohort default rates taken into consideration, but not used to calibrate scenarios Fitch Ratings private student loana default index taken into consideration, but not used to calibrate scenarios
Commona 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 thana valuation, as well as due toa the NAIC's use o data for their RBC framework

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

‡

± 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.

‡

± 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.

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Average deal balance	$534M	$489M
10^{th} –90^{th} percentile	$350M - 902M	$304M - $735M
Average residual thickness	20%	24%
10^{th} –90^{th} percentile	10%-35%	12%-35%
2021 vintage	40%	33%
2022 vintage	20%	24%
2023 vintage	40%	43%

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	

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

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

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

BVABS 2023-CAR2 aka BOF URSA VII Funding Trust I	2023
CarMax Auto Owner Trust 2021-1	2021

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