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RATING METHODOLOGY

Moody's Approach to Rating US RMBS Using the MILAN Framework

This rating methodology replaces *Moody's Approach to Rating US RMBS Using the MILAN Framework* published in August 2021. In this update, we clarified in the "Cash Flow Model" section our structural analysis of warehouse RMBS transactions, and we added an appendix that describes the analysis for warehouse RMBS transactions and adjustments applied for wet loans. We also added a section that mentions our approach to evaluating the risk from environmental, social and governance considerations, and we made limited editorial changes to enhance readability.

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Introduction

This rating methodology describes our approach to rating and monitoring US residential mortgage-backed securities (RMBS) backed by government-sponsored enterprise (GSE) and private label first-lien mortgage loans. The methodology's scope is limited to those transactions with loans originated during or after 2009. For loans originated prior to 2009, we use the US RMBS surveillance methodology, the FHA-VA US RMBS surveillance methodology, or the methodology for rating securities backed by non-performing and re-performing loans.

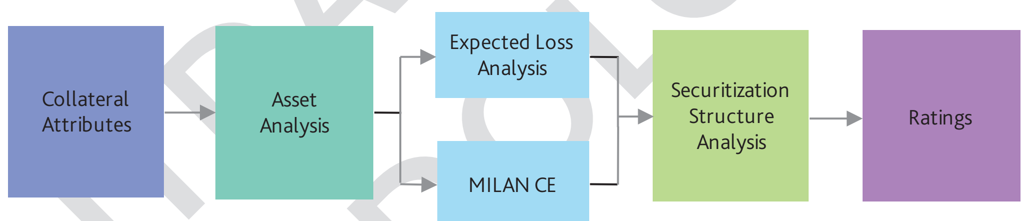
Under our approach, we first conduct an asset analysis in which we perform a loan-level assessment of the securitized collateral portfolio. We aggregate the results of that analysis to derive both the portfolio's expected losses (Portfolio EL) and Moody's Individual Loan Analysis credit enhancement (MILAN CE). The Portfolio EL reflects the loss we expect the portfolio to incur in conditions consistent with the baseline economic forecast, while the MILAN CE reflects the loss we expect the portfolio to incur in a severe economic scenario (the Aaa scenario) generally more stressful than the economic conditions experienced in 2007-2009.

The Portfolio EL and the MILAN CE inform our specification of a collateral loss distribution, which we typically assume to be lognormal. This distribution associates a probability with each potential future loss scenario for the portfolio. The MILAN CE may be different from the credit enhancement that is consistent with a Aaa (sf) rating for a tranche in a specific transaction since the MILAN CE does not take into account the structural features of the transaction.

In our analysis of the transaction's structure, we use a cash flow model to assess the structural features of the transaction based on a discrete number of scenarios drawn from the collateral loss distribution.

Finally, we assess the transaction's overall legal and structural framework before assigning the ratings. As with all rating methodologies, in applying this methodology we will, where appropriate, consider other factors that we deem relevant to our analysis. This includes qualitative considerations such as origination quality, third-party diligence report results, and the strength of representation and warranty frameworks and servicing arrangements, among others. As transactions season, some of the methodology criteria, such as the origination quality review, become less relevant to the analysis, while others, such as collateral performance, could become more relevant. If actual performance or performance trends are not in line with the assumptions described in this methodology, we will reflect that in our analysis. We outline our methodology framework in Exhibit 1.

EXHIBIT 1
RMBS Rating Methodology*



* The various steps may incorporate qualitative considerations such as origination quality review, third-party diligence report results, the strength of representation and warranty frameworks and servicing arrangements, sovereign risk, counterparty risk, deal structure, and other committee considerations.
Source: Moody's Investors Service

Asset Analysis

Overview

When rating US RMBS using the MILAN framework, we first analyze the portfolio of mortgage loans. This analysis combines features of the loan and borrower (collectively known as "loan-level characteristics") with assumptions about the economic environment the loan will experience. The loan-level characteristics that inform our quantitative modeling are outlined in our description of the MILAN model in Appendix 1. Examples of typical information used to assign and monitor ratings under the MILAN framework are listed in the US parameter settings that can be found in Appendix 8.

The results of this asset analysis are the Portfolio EL and the MILAN CE.

» **Portfolio EL** reflects the loss that we expect the portfolio to incur under the baseline economic projected outlook. Details of the baseline economic forecast that we use are described below. We use the US MILAN model to help derive our Portfolio EL estimates, though we may incorporate other considerations, such as historical performance, as well.

» **MILAN CE** reflects the stressed loss we expect the portfolio to incur in the event of a severe economic scenario, with adjustments for the geographic and borrower concentration of the portfolio.[1] Details of our severe economic scenario are described below. We use the US MILAN model to help derive our stressed loss estimates, though we may incorporate other considerations as well. In our analysis of the transaction structure, the MILAN CE roughly corresponds to the credit enhancement consistent with a Aaa (sf) rated tranche.[2]

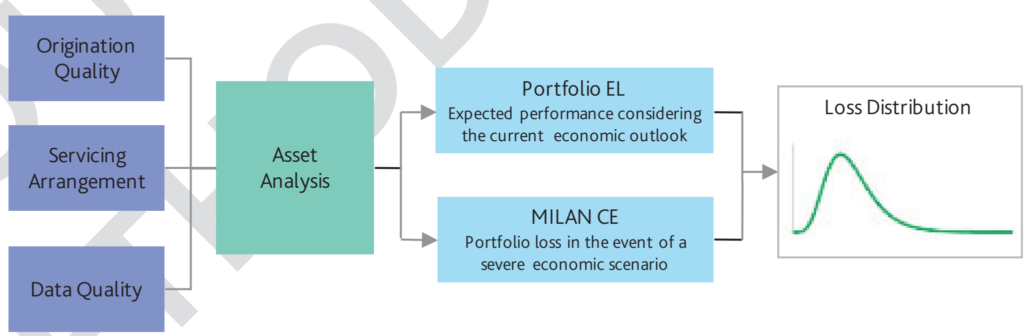
We may adjust the Portfolio EL and MILAN CE to take into consideration our review of the (i) origination quality; (ii) servicing arrangement; and (iii) data quality which includes representations and warranty framework and third-party diligence report results. We may not update all of these evaluations for frequent issuers whose origination and servicing practices have not changed materially. Some of these considerations, such as origination quality, could also be less relevant as transactions season and performance information becomes available.

We use the two outputs from our asset analysis (Portfolio EL and MILAN CE) to specify a collateral loss distribution. This distribution associates a probability with each potential future loss scenario for the portfolio. For RMBS portfolios, we typically assume the collateral loss distribution is lognormal. (See Appendix 2.)

Our asset analysis assesses the range of possible losses the portfolio will ultimately incur, assuming transaction parties perform as intended. However, other events, such as a counterparty default, could cause additional collateral losses. We assess these additional losses in our analysis of the structure, which we describe later in this report. We also assess the impact of the timing of portfolio losses and prepayments as part of our analysis of the structure.

EXHIBIT 2

Asset Analysis



Source: Moody's Investors Service

Deriving the MILAN CE and EL

We generally use the US MILAN model to evaluate the collateral and derive the MILAN CE.[3] The model provides an assessment of individual loans as well as overall portfolio diversification, estimating the portfolio's loss in a severe economic downturn scenario (the Aaa scenario), with adjustments for borrower and geographic concentration. The final MILAN CE takes into account the calculated model result and any

1 To calculate borrower concentration, we typically assume that each borrower has only one loan in the pool, although we may adjust this assumption if deemed appropriate.

2 The MILAN CE may be different from the credit enhancement that is consistent with a Aaa (sf) rating for a tranche in a specific transaction since the MILAN CE does not take into account the structural features of the transaction.

3 For more information, see the "Ongoing Surveillance, Including Small Residual Portfolios" section.

other qualitative and quantitative aspects of the asset analysis. Appendix 1 contains a step-by-step guide to our collateral analysis.

We define our Aaa scenario with respect to local and national house price changes, local unemployment rate changes, and interest rate levels. We specify the path of each of those variables from the time of loan origination to the point of our analysis and from that point into the future. Below we describe the central assumptions of our Aaa scenario, which are based on the economic experience in 2007-2009 when a steep decline in house prices triggered a financial crisis.

We use the same general approach to derive both the Portfolio EL and the MILAN CE; the primary difference is the economic assumptions used in the model. For purposes of estimating the expected portfolio loss, we typically use the baseline forecasts of national and local metropolitan statistical area (MSA)-level house price indices, local MSA-level unemployment rate changes, and interest rates provided by Moody's Economy.com (MEDC).[4] We further incorporate the realized path of those variables since loan origination.[5] The resulting loss – the expected portfolio loss conditional on baseline economic paths – is interpreted as the median portfolio loss.

The measures of portfolio concentration that can directly affect the MILAN CE model output do not affect the Portfolio EL. This is because concentration introduces correlated risks and increases our uncertainty regarding ultimate collateral performance, but it does not directly impact the level of losses we expect as a central tendency of the portfolio.

The quantitative model output can be refined by an analysis of historical performance and benchmarking against comparable portfolios as well as other considerations to finally determine the Portfolio EL and MILAN CE.

House Price Changes

In the Aaa scenario, we reflect in our property value assumptions the realized national house price changes from the date of loan origination to the analysis date, as provided by MEDC;[6] however, we cap any appreciation at 2% per year, meaning we do not give credit if prices have appreciated more than that. If prices have declined, we would account for the full extent of the decline without any floor. We assume that individual property values have followed that path from the time of closing of their respective loan to the analysis date. We then assume that individual property values follow the stressed local house price path into the future.[7]

We assume that from the time of our analysis forward, the national house price index declines 30% over a 30-month period, remains flat for the following 30 months, gradually rises over the following 120 months to the level at the time of our analysis, and then continues to appreciate at 3% per year.[8] This approximates, but is generally more stressful than, the path of national house prices from July 2007 forward.

We assume that the local MSA-level house price index declines by 30% to 60% (depending on the geographic concentration of the pool) over a 30-month period, remains flat for the following 30 months, gradually rises over the following 120 months to the level at the time of our analysis, and then continues to

4 These forecasts are updated on a monthly basis. To achieve stability in our Portfolio EL estimates, we typically use the average of the six most recent forecast sets.

5 Macroeconomic data (historical and forecast) are subject to revisions; therefore the data that we use in our models may change over time.

6 We refer to the national path of house price changes, instead of the MSA-level path, to assess realized price changes in our Aaa scenario because it aims to represent a stylized stress scenario that does not differentiate by MSA. We then factor in MSA concentration with our concentration adjustment, which drives the MSA-level projected house price declines, as discussed more in detail later in this methodology.

7 Note that the level of local house prices is not a factor in our model, only its path since loan origination. Individual property values are used to determine the path of the cumulative loan-to-value ratio as well as in our loss-given-default modeling.

8 Note that the level of national house prices is not a factor in our model, only its path since loan origination.

appreciate at 3% per year. The property value assumptions are adjusted by the change implied by the house price index as projected under this stress scenario.

In the expected baseline scenario, we use historical and forecast data on house price changes at the MSA level, as provided by MEDC, to update our property value assumptions since loan origination.

Unemployment

In the Aaa scenario, we assume that from the time of our analysis forward, the local (MSA-level) unemployment rate rises by an aggregate five percentage points (linearly) over a 30-month period, remains at that elevated level for the following 30 months, declines over the following 120 months to the level at the time of our analysis, and then remains constant. This approximates, but is generally more stressful than, the path of the national unemployment rate from July 2007 forward. We assume that local unemployment has remained unchanged since the loan was originated to the point of our analysis.[9]

In the expected baseline scenario, we consider the historical and forecast change in MSA-level unemployment since loan origination.

Interest Rates

In the Aaa scenario, we assume that the 30-year Freddie Mac index rate (the "market rate") remains flat after loan origination. This is stressful for the default probability relative to the experience of 2007-2009 during which this interest rate fell sharply. We also assume that a generic "reference rate" to which any adjustable-rate mortgage (ARM) is indexed similarly remains flat and at a level 100 basis points below the market rate.[10]

While the level of the market rate does not enter our quantitative models directly, our models do incorporate the difference between a loan's rate and the market rate. This "prepayment incentive" spread is a critical driver of prepayment risk and hence default risk. We, therefore, make an assumption regarding the level of the market rate for purposes of calculating that spread; alternatively, we must make an assumption on the value of that spread which then implies a level for the market rate. For fixed-rate mortgages (FRM), we assume that the "prepayment incentive" is exactly zero in the Aaa scenario, meaning that we assume the market rate is the same as the loan rate for FRMs. For ARMs, we assume that the market rate remains flat at its level during the first full month for the remainder of the loan's life.

The level of the reference rate does not enter our quantitative models directly; however, it is needed to determine the level of an ARM's rate upon reset. By assuming that the generic reference rate is 100 basis points below the market rate, we are effectively assuming that an ARM with a 225 basis-point spread to index (the most common index spread we observe) will reset to a rate that is higher than the prevailing market rate. While this creates a positive prepayment incentive for most ARMs upon reset, it also represents a significant payment stress as their effective interest rate increases.

In the expected baseline scenario, we use interest rates based on the most recent forecasts provided by MEDC. The prepayment incentive is calculated per the prevailing mortgage rates provided by MEDC.

Calibration Factor

Our quantitative models include a calibration variable that is intended to capture the "unknown" aspects of performance not otherwise explained by the observed variables. The value of the calibration factor is derived from the 12-month leading and lagging house price appreciation/depreciation at the time of origination and it may relate to market practices, such as lending standards at the time of origination and other business

[9] Note that the level of the unemployment rate is not a factor in our model, only its path since loan origination.

[10] Note that in our Aaa scenario we generally do not distinguish between different index rates.

considerations affecting the origination of the loans. In our Aaa scenario, we assume a calibration factor equal to that calculated as of July 2007.[11]

Under the baseline scenario, the calibration factor is set to values based on the loan origination date. In an environment where house prices appreciate, the calibration factor in the baseline scenario is zero.

Concentration Adjustments

Our quantitative models include an adjustment for the concentration of the portfolio. Details are presented in Appendix 1. Concentration is defined with respect to both borrower and geographic concentration, with the latter defined at both the ZIP code and MSA level. In all cases, the degree of concentration is measured by the portfolio's "effective number" (strictly, the reciprocal of the Herfindahl Index)[12] measured by the borrower, ZIP code, or MSA aggregations.

The MSA effective number drives our assumption on the degree of local house price depreciation. If the portfolio were, hypothetically, located in one MSA, we would stress local property prices by a 60% decline; if the portfolio has 30 or more effective MSAs, we would stress local property prices by a 30% decline, just as we do for national prices. If the portfolio has an intermediate number of effective MSAs, the local property decline is given by an average decline which assumes that one MSA has a 60% decline and all other MSAs have a 28.97% decline.[13] For example, if the effective number were two, we would assume an average decline of 44.5%.

Beyond determining the degree of local house price stress, the model loss under the Aaa economic scenario is adjusted if (1) the effective number of borrowers is less than 3,000, (2) the effective number of ZIP codes is less than 3,000, or (3) the effective number of MSAs is less than 60.

Forecast Horizon of the MILAN Model

In general, we run our loss projections over the life of the loans in the transaction. If the transaction's legal final maturity occurs before the scheduled maturity of all the assets, which may be the case for certain synthetic risk transfer deals, we typically use a forecast horizon that corresponds to the remaining life of the transaction.

Minimum CE

The MILAN CE is typically subject to a floor that is equal to the median portfolio loss (the baseline scenario loss) multiplied by the Aaa multiples. The multiples are similar to those used in the US RMBS surveillance methodology. The multiples differ based on the level of the median portfolio loss assumed and typically vary between 1.6 (for high portfolio loss, 50%) and 6.5 (for low portfolio loss, 1%).

Origination Quality

Our origination quality review[14] generally consists of a review of the originator's underwriting guidelines, past loan performance, and its policies and practices that could affect future loan performance. We use the review of the origination quality to adjust our assumptions when appropriate since originator-specific practices could affect future loan performance. The adjustments can be made at the loan level or transaction level. This review becomes less relevant as transactions season and performance data become available.

11 The July 2007 vintage calibration factor is approximately 0.25 for default risk and approximately 0, or "standard," for prepayment risk.

12 The Herfindahl score is the inverse of the Herfindahl-Hirschman Index or HHI.

13 Under this formulation, the average decline for a portfolio with an effective number of MSAs of 30 would be exactly 30%.

14 The origination quality review includes the review of an aggregator's criteria and practices, if applicable.

Servicing Arrangement

Our analysis also accounts for the impact of servicing arrangements on the performance of mortgage loans. In general, the impact of a servicer's strategy, policies, and practices on the performance of its loans largely depends on the credit profile of the underlying borrowers.

In transactions backed by loans to prime quality borrowers, we expect servicing activities to focus on core functions such as processing payments and reporting loan performance, both of which tend to be automated features of the servicing platform. Once a servicer establishes its ability to perform these core servicing functions, absent a significant change in its servicing platform or a significant deterioration in the transaction's performance, we expect these servicer-specific procedures to have a neutral effect on pool performance. Because these core servicing activities are central to all servicing platforms, they are also easily transferrable to other RMBS servicers.

For non-prime transactions, a servicer's experience with respect to non-performing loans is more important than for prime transactions. In addition to providing the core functions described above, servicers that can provide frequent contact with borrowers and are proactive in loss mitigation can help reduce foreclosure timelines, minimize expenses, and maximize recoveries to RMBS trusts.

We typically consider servicing arrangements, such as the presence and obligations of any entity overseeing the performance of the servicer (for example, a master servicer or special/sub-servicer) and the servicing fee structure, and adjust our assumptions when appropriate. When modeling servicing arrangements where servicing fees are a function of loan status and a servicer's loss mitigation activities, we also assess whether a transaction's fee structure would be sufficient to attract a successor servicer, if needed, and based on our assessment we may stress the servicing fees accordingly.[15] Other adjustments could result from risks related to a servicer's lack of procedures to protect mortgage liens from homeowner association foreclosures or other risks related to property protection. The adjustments can be made at the loan level or transaction level.

Our cash flow analysis considers servicing arrangements such as when a servicer does not advance interest and principal payments for delinquent borrowers or does so for a limited duration (stop-advance features). Stop-advance features may introduce an increased risk of an interest shortfall on the rated bonds for transactions where principal collections or liquidation proceeds cannot be used to pay interest on the bonds and where no alternative source of liquidity to pay interest is available.

Nevertheless, stop-advance features may also lessen potential cash flow disruptions upon advance recoupment, offer greater transparency, and reduce the impact of a servicer's actions on the senior bonds in certain high-stress scenarios. Stop-advance arrangements are more transparent because the ongoing remittance reporting shows that the cash available to pay down the bonds is from the collections rather than servicer advances. Furthermore, stop-advance features may help align the incentives of the servicer to the interests of senior bondholders through a speedier resolution of delinquent loans. As a result, we may run alternative cash flow scenarios or reduce the MILAN CE for transactions with such alignments.[16]

Data Quality

A key element of our asset analysis is an evaluation of the mortgage loan characteristics. In assessing those characteristics, we typically rely on data provided by the sponsor of the transaction. Consequently, our assessment depends on whether the data are likely to provide an accurate representation of the loan characteristics. To assess the quality of the data the sponsor provides at the time of initial ratings, we review

[15] In transactions where the sponsor is also the servicer and is a highly rated entity, we would generally apply the transaction fee structure and would not stress it because the likelihood of a servicing transfer is low.

[16] However, servicer advances for property preservation, taxes, insurance, and similar expenses are necessary for lien preservation.

the origination quality, obtain third-party diligence reports, and analyze the representations and warranties of the transaction. Based on our assessment of the data quality, we may adjust our assumptions at the loan level or transaction level, when appropriate.[17] For details on our data quality analysis for US RMBS transactions, please refer to Appendix 4.

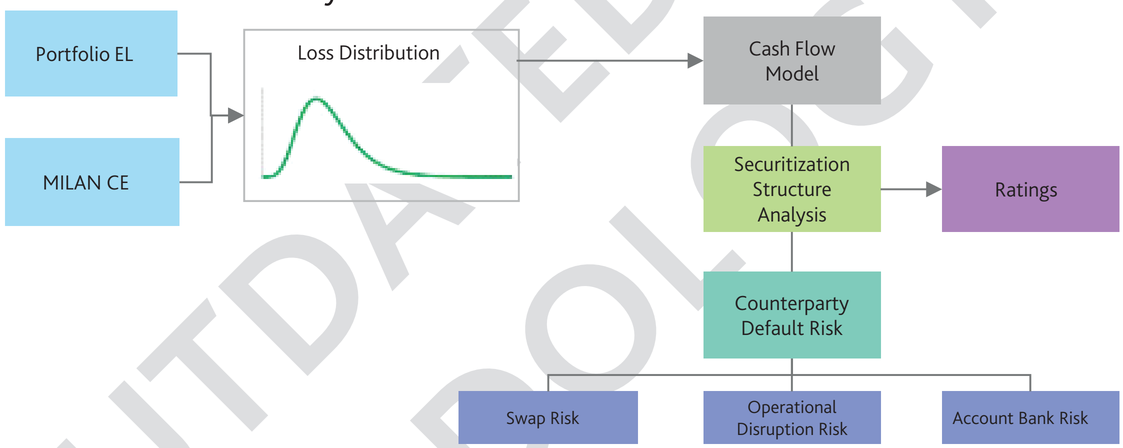
Securitization Structure Analysis

Overview

In order to analyze the structure of a transaction, we use a cash flow model to assess the impact of the transaction's assets and liabilities on the potential losses to investors. The model calculates each tranche's expected loss, which we use in conjunction with the pool's assumed average life as the basis for a model output.

EXHIBIT 3

Securitization Structure Analysis



Source: Moody's Investors Service

Cash Flow Model

We use a cash flow model to assess the major features of a transaction's liability structure in conjunction with asset performance. See Appendix 3 for details of our cash flow assumptions.

We base our ratings of RMBS tranches on the expected losses (Tranche EL) that investors could incur by the legal final maturity. The Tranche EL considers both the probability and the severity of credit losses that investors could incur.[18]

To determine the Tranche EL, the cash flow model calculates the loss to investors resulting from each portfolio loss scenario of the loss distribution. The model then weights each loss with the corresponding probability of the loss scenario and aggregates the weighted losses to calculate the tranche's expected loss. We combine the Tranche EL with a calculated portfolio average life[19] to derive the model-implied output based on a mapping table, our Idealized Expected Loss table.[20]

17 For more information, see our methodology for evaluating data quality in structured finance transactions. A link to a list of our sector and cross-sector methodologies can be found in the "Moody's Related Publications" section.

18 For more information, see *Rating Symbols and Definitions.* A link can be found in the "Moody's Related Publications" section.

19 Calculated excluding defaulted loans.

20 For more information, see the discussion of Idealized Probabilities of Default and Expected Losses in *Rating Symbols and Definitions*. A link can be found in the "Moody's Related Publications" section.

Securitization Structure Analysis

In analyzing the structure of a transaction, we consider the following elements:

» **Assumptions about asset performance, such as:**

– **Loss timing**: For each loss scenario drawn from the collateral loss distribution, the cash flow model incorporates one or more loss-timing scenarios. We detail these assumptions in Appendix 3. The number of scenarios that we use varies depending on the sensitivity of the transaction to timing differences, which depends on the transaction's structure.

– **Prepayment rates, prepayment timing and amortization**: We use both the scheduled amortization of the portfolio and a prepayment rate assumption in our cash flow modeling. We might also run multiple prepayment scenarios for each of the loss scenarios. We provide details of these assumptions in Appendix 3.

– **Interest rates and swaps**: In transactions that are not fully hedged (i.e., floating-rate liabilities backed by fixed-rate assets or fixed-rate liabilities backed by floating-rate assets), and where the notes are not subject to a net weighted average coupon (WAC) cap, we generally stress the interest payable on the notes or haircut the interest payable by the assets. For this purpose, we typically size the stress or haircut in accordance with the principles in our approach to assessing the impact of linkage to swap counterparties,[21] with adjustments as necessary to address the nature of the unhedged risk.

– **Substitutions**: For revolving transactions, we take into account the length of the substitution period and any anticipated changes to the overall asset yield that could result from new assets being added to the portfolio. We model the estimated losses for the substituted assets based upon the substitution criteria and our views on the credit quality of the potential additions.

– **Term and market value risk:** For revolving transactions, such as warehouse RMBS transactions, we also consider the term of the warehouse and the effectiveness of features to mitigate potential market-value risk (such as the mark-to-market criteria for the mortgage loan portfolio and the collateral auction process).

» **Transaction-specific structural features**: The cash flow model incorporates transaction-specific structural features, such as priority of payments and losses, collateral performance triggers/credit enhancement floors, excess spread, servicer advancing, servicing fees waterfall and other specific features.

[21] For more information, see our cross-sector methodology for assessing counterparty risks in structured finance, including swap linkage. A link to a list of our sector and cross-sector methodologies can be found in the "Moody's Related Publications" section.

» **Loan concentration risk considerations (for shifting interest/pro rata structures)**: To further consider the possible impact of concentration risk at the tail end of a transaction, we assess the sufficiency of any credit enhancement floors proposed in the structure at the time of initial rating analysis. We calculate the credit-neutral floors for a given target rating as shown in the table below; for example, for a Aaa (sf) target rating, the floor is equal to an amount which is the sum of the balance of the six largest loans at closing multiplied by the higher of their corresponding MILAN Aaa severity or a 35% severity. If the proposed floors are below the credit-neutral floors, depending on the pool characteristics and/or securitization structure, we may either perform additional analysis to determine the sufficiency of the floor or assign a rating corresponding to proposed floors as per the grid below.

EXHIBIT 4

Credit-Neutral Floor

Bond rating	No. of largest loans	Severity applied to the largest loans
Aaa (sf)	6	Greater of MILAN Aaa severity or 35%
Aa1 (sf)	5	Greater of MILAN Aaa severity or 35%
Aa2 (sf)	4	Greater of MILAN Aaa severity or 35%
Aa3 (sf)	3	Greater of MILAN Aaa severity or 35%
A1 (sf)	2	Greater of MILAN Aaa severity or 35%
A2 (sf)	1	Greater of MILAN Aaa severity or 35%
A3 (sf)	0	NA

Source: Moody's Investors Service

Exhibit 5 sets forward an illustration of the credit-neutral floors.

EXHIBIT 5

Illustrative Example of Credit-Neutral Floors

Suppose:

» MILAN Aaa severity = 25%*

» Severity applied to the largest loans = Max (25%,35%) =35%

» Proposed senior floor = 1.9%

» Proposed subordinate floor = 0.5%

» Senior class target rating = Aaa (sf)

» Junior class target rating = A1 (sf)

» Aaa credit-neutral floor = % top 6 loans * Severity = 6% * 35% = 2.1%

» A1 credit-neutral floor = % top 2 loans * Severity = 2%* 35% = 0.7%

Bond rating	No. of largest loans	% top loans over pool balance	Severity	Credit-neutral floor
Aaa (sf)	6	6%	35%	2.10%
Aa1 (sf)	5	5%	35%	1.75%
Aa2 (sf)	4	4%	35%	1.40%
Aa3 (sf)	3	3%	35%	1.05%
A1 (sf)	2	2%	35%	0.70%
A2 (sf)	1	1%	35%	0.35%

* For simplicity we assume in this example that all the top 6 loans have the same MILAN Aaa severity of 25%.

Source: Moody's Investors Service

Exhibit 4 applies to shifting interest and pro rata structures.[22] We may use a different approach to calculate the credit-neutral floors if the pool characteristics, securitization structure, or both are significantly different from typical shifting interest and pro rata transactions, and we may consider the floor on a case-by-case basis.[23]

» **Other risks**: Our cash flow analysis also incorporates the effects of other structural features that cause risks or are designed to mitigate risks, such as the nature of the interest promise on the bonds and the interest shortfall recoupment mechanism.

Assessing Counterparty Default Risks

The structural analysis incorporates assumptions about certain risks relating to counterparty default. We assess the extent to which non-performance by any counterparty in a transaction could pose risk to investors. As part of that assessment, we may analyze the role of the counterparty (such as the servicer, cash manager, swap counterparty), its ability to carry out its role, its operational and financial stability, and back-up mechanisms incorporated into the transaction. As a result of the analysis, rating committees may supplement model output with transaction-specific rating caps.[24]

We evaluate other operational protections and elements such as covenants, triggers and events of default to mitigate operational risk associated with key transaction parties.

Additional Structural Analysis: Legal Risk

As part of our analysis of legal risk, we generally review the transaction documents and legal opinions to assess the extent to which the transaction's legal framework addresses the risks associated with, for example, bankruptcy remoteness, the assignment of the assets to the trust, the enforceability of the transaction provisions, and tax matters related to the transaction, as applicable.

Ongoing Surveillance, Including Small Residual Portfolios

For surveillance of US RMBS transactions backed by GSE and private label first-lien mortgage loans originated during and after 2009, we generally follow the key applicable components of the approach described in this report. For the model-based asset analysis, we update relevant model inputs using loan-level information and updated economic data and forecasts to reassess the Portfolio EL and MILAN CE.

As a transaction becomes more seasoned, some of the adjustments we make at the time of initial ratings may become less relevant because the transaction accumulates actual performance data. Therefore, we phase out certain adjustments (for example, origination quality adjustment, and representations and warranties adjustment) over time, reducing them to zero.

We typically receive relevant data on transaction-specific performance, which we use to monitor transactions. For transactions backed by seasoned loans for which we have significant performance information available, we can directly leverage the available performance information for our analysis. In these circumstances, borrowers' payment patterns may be better predictors of default than initial loan

22 Transactions that pay junior tranches sequentially effectively provide floors that are typically significantly higher than the credit-neutral floors described in Exhibit 4.

23 For example, if the pool has a significantly lower MILAN implied probability of default (MILAN PD) than typical shifting interest and pro rata pools and was originated by an entity which has demonstrated strong performance over an extended period of time, we could calculate an alternative floor based on a higher number of loans defaulting at the Aaa PD (instead of 100% PD).

24 For more information, see our methodology that discusses our approach to assessing counterparty risks in structured finance. A link to a list of our sector and cross-sector methodologies can be found in the "Moody's Related Publications" section.

credit characteristics that have not been updated. In these cases, we may use alternate approaches that use the available updated performance data to forecast future expected and stressed losses.

The performance information data fields that we typically expect to receive to monitor ratings are included in our US parameter settings. If certain fields or data are not provided, we may apply more conservative assumptions on a case-by-case basis. If loan-level data ceases to be available, we may use the aggregated pool performance and tranche-level information in performing our analysis, including deriving the Portfolio EL from the pool performance and applying the expected loss multiples to derive the MILAN CE. If the information is insufficient to effectively perform our analysis, we may withdraw the ratings in accordance with Moody's Policy for Withdrawal of Credit Ratings.

While we generally apply the quantitative modeling framework described herein for monitoring purposes, we may make adjustments to reflect loan-level performance information. For a loan that we deem to be already in default, we generally only conduct a loss-given-default analysis. For a modified loan, we assume a higher liquidation probability[25] than would otherwise be the case.

In cases when actual performance significantly diverges from initial model expectations of the pool's performance (for example, as evidenced by performance data on serious delinquencies, defaults, modifications, losses, or all four), the model will adjust the calibration factor and consequently our Portfolio EL and MILAN CE floor to reflect that divergent performance.[26] When assessing actual performance to determine whether it diverges from initial model expectations, the model applies certain roll rates to delinquent and modified loans that indicate the percentage of borrowers in each of those categories that we expect to ultimately default. The more severe the delinquency, the lower the likelihood of curing and thus the higher the resulting roll rate. Such roll rate assumptions are based on historical observed trends which can change over time.

We typically perform a structural analysis that considers the cash flow model result using the updated capital structure. However, the monitoring of certain transactions may not always warrant updated cash flow model analysis; for example, for transactions where all the tranches have a credit enhancement materially higher than the MILAN CE.[27]

In addition, if transaction performance deteriorates to an extent that the model output no longer reflects our view of future performance, we may use an alternative approach to estimate the Portfolio EL and MILAN CE. Also, in limited instances where cash flow waterfalls are not available due to insufficient data, we may use a static method where we compare our expected losses on the underlying pool to each bond's total credit enhancement, including excess spread, subordination, overcollateralization, and any other form of internal or external credit support (loss coverage analysis).

25 In calibrating the model, we treated modified loans as defaulted. When forecasting the liquidation probability for modified loans in a pool, however, we typically apply a multiplicative factor to the loan-level MILAN PD.

26 For purposes of comparing realized vs. expected performance, in both cases we assume a 100% default rate for pre-closing modified loans. This is to ensure that the model does not adjust the calibration factor when we are presented with pools that have a meaningful number of pre-closing modified loans. Unlike loans modified after closing, pre-closing modified loans are not indicative of weaker-than-expected transaction performance, and therefore, the presence of pre-closing modified loans should not contribute towards a performance adjustment. This 100% default rate assumption for pre-closing modified loans is only used to assess if the model needs to be recalibrated.

27 For example, in methodologies where models are used, modeling is not relevant when it is determined that (1) a transaction is still revolving and performance has not changed from expectations, or (2) all tranches are at the highest achievable ratings and performance is at or better than expected performance, or (3) key model inputs are viewed as not having materially changed to the extent it would change outputs since the previous time a model was run, or (4) no new relevant information is available such that a model cannot be run in order to inform the rating, or (5) our analysis is limited to asset coverage ratios for transactions with undercollateralized tranches, or (6) a transaction has few remaining performing assets.

Small Residual Pools

As part of our monitoring of RMBS transactions, we also evaluate borrower concentration risk as the portfolios amortize. For small portfolios, a few loans becoming delinquent would greatly increase the portfolios' delinquency rate. If we estimate that the exposure of the notes to a few loans defaulting is not consistent with their ratings, we may adjust these ratings accordingly.

We will not assign nor maintain ratings on securities in a structure[28] with the following characteristics:

» Structures that do not have support mechanisms, such as credit enhancement floors or reserve fund floors: once any of the underlying pool(s) has decreased to an Effective Number[29] of borrowers of 30 or below.[30]

» Structures with reserve fund or credit enhancement floors that partially compensate for the increased exposure to single borrowers: once any of the underlying pool(s) has decreased to an Effective Number of borrowers of 15 or below.[31]

However, we will make exceptions for securities with ratings that do not rely on our assessment of individual obligor creditworthiness, such as those that benefit from a full and unconditional third-party guarantees, whether at the portfolio or note level, or securities with full cash collateralization.[32]

Loss Benchmarks

In evaluating the model output for US RMBS transactions, we select loss benchmarks referencing the Idealized Expected Loss table[33] using the Standard Asymmetric Range, in which the lower-bound of loss consistent with a given rating category is computed as an 80/20 weighted average on a logarithmic scale of the Idealized Expected Loss of the next higher rating category and the Idealized Expected Loss of the given rating category, respectively. For initial ratings and upgrade rating actions, the upper-bound of loss consistent with a given rating category is computed as an 80/20 weighted average on a logarithmic scale of the Idealized Expected Loss of the given rating category and the Idealized Expected Loss of the next lower rating category, respectively. When monitoring a rating for downgrade, the upper-bound of loss is computed as a 50/50 weighted average on a logarithmic scale. That is, the benchmark boundaries of loss appropriate for evaluating rating category R are given by:

FORMULA 1

$$[1]\ Rating\ Lower\ Bound_R = exp\{0.8 \cdot \log(Idealized\ Expected\ Loss_{R-1}) + 0.2 \cdot log(Idealized\ Expected\ Loss_R)\}$$

$$[2]\ Initial\ Rating\ Upper\ Bound_R = exp\{0.8 \cdot \log(Idealized\ Expected\ Loss_R) + 0.2 \cdot log(Idealized\ Expected\ Loss_{R+1})\}$$

28 A structure is a group of securities that share support.

29 The effective number (EN) is a measure of the portfolio diversity that looks beyond the nominal number of borrowers in a portfolio to take into account the actual size of their loans and express this number in terms of equally sized exposures. The EN of n Borrowers = $1/\sum_{i=1}^{n}(W_i)^2$, where Wi is the weight of borrower i in the total portfolio.

30 If we cannot obtain the effective number of borrowers, we will use a threshold of 45 actual borrowers instead. If we do not have the actual number of borrowers, we will use the effective number of loans instead.

31 If we cannot obtain the effective number of borrowers, we will use a threshold of 25 actual borrowers instead.

32 However, for structured finance securities with full support from a financial guarantor, if the financial guarantor's rating is below investment grade, we would not make an exception for a small residual pool and withdraw the rating of the security after withdrawing its underlying rating.

33 For more information, see the discussion of Idealized Probabilities of Default and Expected Losses in *Rating Symbols and Definitions*. A link can be found in the "Moody's Related Publications" section.

$$[3]\ Current\ Rating\ Upper\ Bound_R = exp\{0.5 \cdot \log(Idealized\ Expected\ Loss_R) + 0.5 \cdot log(Idealized\ Expected\ Loss_{R+1})\}$$

Where:

- *Rating Lower Bound$_R$* means the lowest Idealized Expected Loss associated with rating *R* and the expected loss range of rating *R* is inclusive of the *Rating Lower Bound$_R$*.
- *Initial Rating Upper Bound$_R$* means the highest Idealized Expected Loss associated with rating *R* that is either initially assigned or upgraded and the expected loss range of rating *R* is exclusive of the *Rating Upper Bound$_R$*.
- *Current Rating Upper Bound$_R$* means the highest Idealized Expected Loss associated with rating *R* that is currently outstanding and the expected loss range of rating *R* is exclusive of the *Rating Upper Bound$_R$*.
- *R-1* means the rating just above *R*.
- *R+1* means the rating just below *R*.
- The Rating Lower Bound for Aaa is 0% and the Rating Upper Bound for C is 100%. These are not derived using the formula.

Source: Moody's Investors Service

Environmental, Social and Governance Considerations

Environmental, social and governance (ESG) considerations may affect the ratings of securities backed by a portfolio of residential mortgage loans. We evaluate the risk following our cross-sector methodology that describes our general principles for assessing these ESG issues[34] and may incorporate it in our analysis.

[34] A link to a list of our sector and cross-sector methodologies can be found in the "Moody's Related Publications" section.

Appendix 1: Deriving the MILAN Credit Enhancement (CE) for US RMBS

The US MILAN model is a scoring model that assesses the credit risk of US residential GSE-eligible mortgage loan and private label first-lien mortgage loan portfolios in a severe economic scenario we define as the Aaa scenario, or in a baseline economic scenario. There are two versions of the model: one that applies to private label first-lien loans, and one that applies to GSE-eligible fixed-rate loans. The models were calibrated on appropriate data sets, and while they incorporate identical economic drivers and many of the same borrower- and loan-level characteristics, each model incorporates some unique characteristics depending on the information available in its respective estimation dataset.

The Aaa scenario used to assess stressed portfolio losses and derive the MILAN CE is generally more stressful than the economic conditions experienced in 2007-2009. The details of the scenario are available in the US parameter settings that can be found in Appendix 8. The scenario is defined with respect to national and local (MSA-level) house price depreciation, local (MSA-level) unemployment rate changes and interest rates.

The US MILAN model is an application of both a default model (PD Model) and a severity model (LGD Model), which together provide an estimate of the portfolio loss under a given economic scenario. When using a severe scenario, the results are interpreted as the stress loss; when using a baseline or expected economic scenario, the results are interpreted as the expected central tendency (strictly speaking, the median) loss.

The probability of default (PD) and expected loss given default (LGD) for each loan are based on both loan-level characteristics and the economic scenarios. Estimates of portfolio-level losses depend on an aggregation of individual loan-level losses and on adjustments for borrower and regional concentration as appropriate.

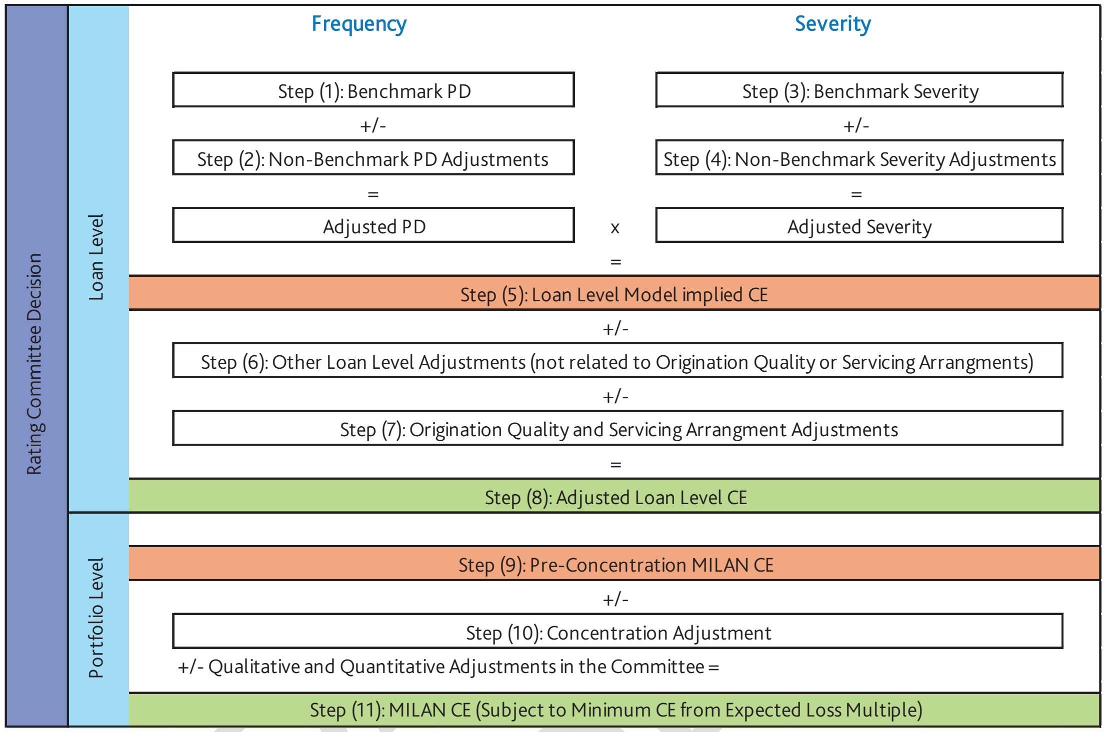
We have a PD and an LGD model for private label and for GSE loans. For GSE-eligible loans included in private label securitizations, we use a hybrid approach to reflect the alignment with key drivers of PD and LGD. For PD, we believe GSE-eligible loans in private label securitizations are more closely aligned to the loans in the GSE PD model because the underwriting for GSE-eligible loans is likely to be consistent regardless of the type of securitization. Originators typically use GSE automated underwriting systems that are subject to GSE underwriting guidelines. For LGD, however, we believe that GSE-eligible loans in private label securitizations are more closely aligned with private label LGD, because LGD (after controlling for loan characteristics) is largely a function of servicing practices.

The GSE model is not calibrated for ARM loans; we analyze GSE-eligible ARMs using the private label model instead to assess the loan PD, which will result in a more conservative outcome than the GSE model. The LGD is not impacted by loan coupon type (fixed or floating).

In Exhibit 6 we provide a summary outline of the steps we follow in the modeling of portfolio losses, starting with default frequency (PD) and severity (LGD). We focus on deriving the MILAN CE, however Portfolio EL calculations follow similar steps, except for the concentration adjustment that does not apply to Portfolio EL.

EXHIBIT 6

Deriving the MILAN CE: A Step-by-Step Guide



Source: Moody's Investors Service

Step (1): Benchmark PD

The first step in the MILAN approach is to calculate the loan's benchmark PD. The benchmark PD for a loan is based on the borrower's FICO score and the borrower's combined loan-to-value ratio (CLTV), assuming all other features of the loan are at the benchmark settings (see Exhibit 7).

EXHIBIT 7

Benchmark Loan Attributes

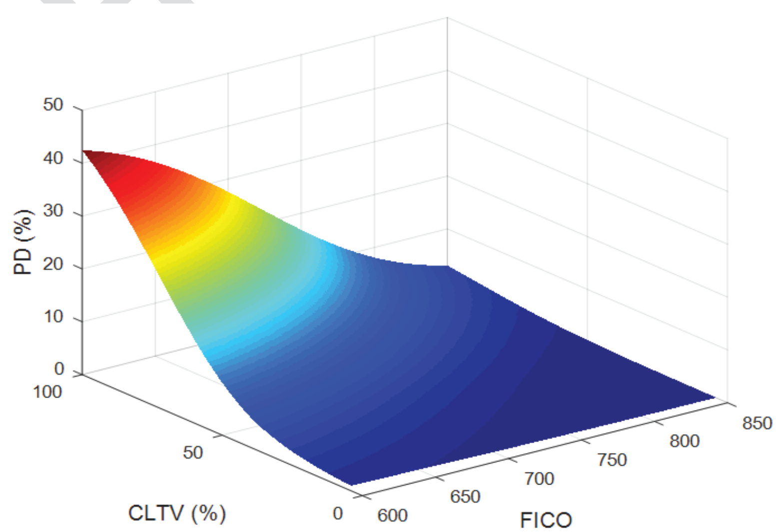
Characteristic	Benchmark Value
Original Term to Maturity	360 months
Original Amortization Term	360 months
Original Interest Only Term	None
Original Prepayment Penalty Term	None
Documentation	Full
Occupancy Type	Owner-Occupied
Property Type	Single-Family
Loan Purpose	Purchase
ARM Loan	No
Seasoning	0 months
Property Value Spread to MSA Median	0
Property Value Spread to US Median	0
Original Interest Rate	5.0%
Credit Spread at Origination	0 bps
Prepayment Spread	0 bps
Judicial State	No
DTI†	40%
Origination Channel Type†	Retail
First-Time Borrower†	No
Number of Borrowers†	1
Number of Units†	1

† Indicates inputs into GSE probability of default model only. For private label loans, these attributes may be considered outside the MILAN model.
Source: Moody's Investors Service

Loans with higher FICO scores or lower CLTV ratios will have lower benchmark PDs. Exhibit 8 shows a representative example of the impact of FICO and CLTV on benchmark PDs. The current benchmark PDs are available in the US parameter settings that can be found in Appendix 8.

EXHIBIT 8

Example of Benchmark Default Probabilities



Source: Moody's Investors Service

Step (2): Loan-level adjustments for borrower and loan attributes

In the second step in the MILAN framework, we use Formula 2 to adjust the benchmark PD for any loan-level attributes (whether attributes of the borrower or the loan) that deviate from the benchmark settings.

FORMULA 2

$$PD_{Adj} = PD_{Unadj} \; x \; P_1 \; x \; P_2 \; x \ldots P_N$$

Where:

» PD_{Unadj} is the PD from Step 1

» $P_1, P_2, \ldots, P_N$ are adjustments for loan, borrower and property characteristics that deviate from the benchmark characteristics shown in Exhibit 7.

Source: Moody's Investors Service

In the US framework, the penalty for a given attribute will generally depend on all of the characteristics of the loan taken together. Therefore, we cannot determine analytically the exact value of a penalty for a given loan in advance. However, we can determine the typical range for a penalty, available in the US parameter settings that can be found in Appendix 8. Because these are multiplicative penalties, a value of one represents no change to the PD associated with that loan characteristic; a value greater than one indicates that the PD is increasing with that characteristic; and a value of less than one indicates that the PD is decreasing. The PD model is an econometric model and as such, the adjusted PD in Formula 2 incorporates historical correlations across attributes and is not duplicative for different factors. The penalties are a decomposition for presentation and attribution analysis.

When analyzing a loan, the adjustment for a given attribute could in some instances fall outside the range shown in the US parameter settings, depending on the precise combination of loan characteristics. Also, even though the supplement shows the indicative adjustment ranges for the most common loan attributes, it is not an exhaustive list of all possible attribute values.

The following loan attributes, starting with letter A below, are used in the model. The impact of each attribute on the final loan PD is based on general observations and depends on the other loan attributes. Certain attributes are only incorporated within either the private label model or the GSE model because of data availability when estimating those models. We indicate whether the attribute is exclusive to either the private label model or the GSE model.

Since the historical data used to calibrate the models reflect past underwriting practices, our adjustments for some of the below-mentioned loan attributes could vary based on our evaluation of the originator's (or aggregator's) underwriting practices. We may also selectively use the GSE model calculations to inform our adjustments for loan attributes that are exclusively incorporated in that model when analyzing a private label portfolio. Conversely, if certain attributes that are exclusively incorporated in the private label model become pertinent in the analysis of an GSE portfolio, we may selectively use the private label model.

A) ORIGINAL AND CURRENT CLTV

The MILAN model adjusts the loan PD to reflect both the original CLTV as well as its current updated value. To produce the updated CLTV, the model assumes that the loan amortizes from its current balance[35] according to the terms of the loan and that the property value follows the assumed path of local house prices. Default risk generally increases as CLTV increases, both original and current.

[35] As a result, if a loan has partially prepaid, it receives credit in our quantitative analysis through an updated CLTV calculation. Similarly, if a loan has amortized more slowly than its terms would suggest, it is penalized through the same process. We assume all the liens amortize according to the terms of the first lien.

B) ORIGINAL FICO

The MILAN model adjusts the loan PD to account for the borrower's original FICO. Default risk generally decreases as FICO increases. When available, we may choose to use an updated FICO score in place of the original score. In addition, we may qualitatively decide to increase our Portfolio EL and MILAN CE due to mortgage loans with borrower FICO scores below 600 on a case-by-case basis, depending on the concentration of such loans in an RMBS transaction.

For private label transactions, to accommodate instances when a small portion of a pool is missing FICO scores, we estimate missing FICO scores based upon a regression analysis that incorporates observed loan characteristics, such as the CLTV, the credit spread at origination (SatO) and other factors. For mortgage loans with missing FICO scores, we will request information from the originator to better understand why the FICO scores are missing and the circumstances in which mortgage loans with missing FICO scores are permitted in its underwriting guidelines. We may apply qualitative adjustments if more than five percent of mortgage loans in an RMBS transaction, as of closing based on loan balance, are missing FICO scores.

C) DTI (GSE ONLY)

The MILAN model adjusts the loan PD for GSE loans to account for the borrower's original debt-to-income (DTI) ratio. Default risk generally increases as DTI increases. While DTI is an explicit factor only in the GSE PD model, we may adjust the private label model output to reflect DTI information when it is available.

D) CREDIT SPREAD AT ORIGINATION (SATO)

The MILAN model adjusts the loan PD to account for the loan's SatO. Default risk generally increases as SatO increases. While the absolute level of interest rates reflects many things, the *relative* interest rate that a lender charges a borrower is a strong indicator of risk; lenders generally charge a risk premium consistent with a borrower's credit risk. It is therefore useful to consider how a loan's rate compares to its peers.

SatO is not directly observed but must be inferred. We compare the loan's initial rate with the appropriate market rate at the time of lock-in. For FRMs with legal terms beyond 15 years, we typically use the Freddie Mac 30-year index; for FRMs with legal terms of 15 years or less, we typically use the Freddie Mac 15-year index. For ARMs we typically use the Freddie Mac 5/25 ARM index.

The date of lock-in is typically not known to us. We thus compare a loan's rate to a three-month weighted average of the appropriate market rate to reflect the fact that rates may be locked in anywhere from one to three months (but not generally more than that) before the first full payment month. We may change the weights if rates have generally been increasing or decreasing to reflect the fact that borrowers are more likely to be offered an updated rate when rates have been declining.

Note that we may make adjustments to our estimate of SatO, for example to account for points or fees that affect the mortgage. We may also run additional scenarios to determine a transaction's sensitivity to SatO.

The SatO adjustment in the MILAN model is capped for mortgage loans with high SatO values. However, for pools with large concentrations of high SatO loans, we may increase the Portfolio EL and MILAN CE on a case-by-case basis based on qualitative factors.

E) PREPAYMENT SPREAD

The MILAN model adjusts the loan PD to reflect the current prepayment spread, which is defined as the difference between the loan's rate and the prevailing market interest rate (the Freddie Mac 30-year fixed-rate index). All else equal, when the loan's rate is greater than the market rate (i.e., when the prepayment spread is positive) the borrower has an incentive to refinance the loan to more favorable terms. This tends to lower the probability of default over the long term.

F) ORIGINAL INTEREST RATE

While the loan's interest rate is not an explicit factor in the MILAN model, a loan that carries a lower interest rate amortizes faster than a loan with a higher interest rate, all else equal. Thus, through its influence on CLTV, the MILAN model generally increases the PD with the loan's interest rate.

G) ORIGINAL TERM TO MATURITY

The MILAN model generally reduces the PD for loans with legal terms shorter than 30 years and increases it for loans with legal terms greater than 30 years. The legal term is the loan's term to maturity. Borrowers who opt for loans with shorter legal terms tend to be more risk-averse, given that they take on higher payments in exchange for an accelerated rate of debt reduction. Additionally, shorter maturity loans amortize faster, leading to a faster build-up of borrower equity.

H) ORIGINAL AMORTIZATION TERM (PRIVATE LABEL ONLY)

The MILAN model adjusts the loan PD to account for different amortization periods as these influence the path of CLTV over time. In particular, loans for which the amortization term is greater than the term to maturity (so-called "balloon" loans) are generally subject to an additional stress.

I) ORIGINAL INTEREST-ONLY TERM (PRIVATE LABEL ONLY)

The MILAN model adjusts the loan PD to account for any interest-only (IO) features. Loans with IO features have an initial period of time during which the borrowers pay only the interest on the loans; loan amortization begins only after the IO period has lapsed. The IO term thus affects CLTV over time. In addition to this mechanical effect, we apply adjustments to the loan PD which may be interpreted as a "self-selection" adjustment, reflecting the fact that, historically, IO loans have defaulted at greater rates than could be explained by the impact on CLTV alone.

J) ORIGINAL PREPAYMENT PENALTY TERM (PRIVATE LABEL ONLY)

The MILAN model adjusts the loan PD to account for any prepayment penalty terms. Prepayment penalties result in a charge to borrowers if they prepay their loans before a specified period. A prepayment penalty thus lowers the probability that a borrower will prepay the loan and exit the portfolio. As a result, more of these loans will remain outstanding longer, lengthening the period during which the borrower can default.

K) SEASONING

The MILAN model adjusts the PD for the seasoning of the loan. Generally, the PD decreases as the loan seasons (and still performs).

L) ORIGINAL PROPERTY VALUE

The MILAN model adjusts the loan PD to account for relative property value. Specifically, the model considers the spread of the property value over its MSA median (to reflect whether a property is locally expensive) and its spread over the national median (to reflect whether a property is absolutely expensive). It should be noted that the impact of relative property value is non-monotonic and not equivalent between local and national relative value. That said, default risk is generally lower for properties with lower relative property value at origination, but there can be exceptions, particularly in the extremes.

M) DOCUMENTATION TYPE (PRIVATE LABEL ONLY)

The MILAN model adjusts the loan PD to account for different categories of documentation, increasing the default risk for loans with less than "full" documentation. Note that this is an explicit feature only in the private label PD model, as the GSE PD model was estimated on a sample of only full documentation loans.[36]

N) OCCUPANCY TYPE

The MILAN model adjusts the loan PD to account for different occupancy types. We distinguish between owner-occupied, second homes and investor properties. While a simple inspection of the historical data would suggest that second homes often perform better and investor properties often perform worse than owner-occupied properties, many other loan or borrower features may be different across these different samples. Our model estimates the impact of "occupancy type" combined with CLTV, FICO, SatO, Prepayment Spread and, in the case of GSE loans, DTI. The impact of occupancy type on final loan PD can thus depend on these other attributes.[37]

O) PROPERTY TYPE

The MILAN model adjusts the loan PD to account for different property types. The type of property securing the mortgage has historically correlated with default risk, even after controlling for other loan attributes. RMBS portfolios generally consist of loans collateralized by single-family homes, but could also contain loans collateralized by condominiums, planned unit developments (PUDs), and co-ops. The private label PD model also distinguishes two-to-four-family properties, while the GSE PD model distinguishes manufactured housing properties.

P) LOAN PURPOSE

The MILAN model adjusts the loan PD to account for different loan purposes. Such purposes include purchase loans (typically the least risky) and refinancing loans, the latter of which can be distinguished between those cases for which the borrower is taking out equity for cash (typically the most risky) and those for which the borrower has refinanced for more favorable rates or terms (typically of intermediate risk).

Q) JUDICIAL STATE FLAG

The MILAN model adjusts the loan PD to distinguish between properties located in judicial states from those which are not. All else equal, default risk is greater for a judicial state-based property.

R) CHANNEL TYPE (GSE ONLY)

The MILAN model adjusts the loan PD to account for different loan origination channels. Such channels include retail (the least risk), broker (the most risk) and correspondent (intermediate risk) channels.

S) FIRST-TIME BORROWER FLAG (GSE ONLY)

The MILAN model adjusts the loan PD to distinguish first-time borrowers from all others. An analysis of the historical data suggests that first-time borrowers are less risky, all else equal. Of course, since other features may not be equal, it does not necessarily follow that first-time borrowers are less risky on net balance.

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36 As described in Appendix 6, in certain cases based on qualitative factors, we may increase our Portfolio EL and MILAN CE due to mortgage loans with alternative documentation.

37 For example, in our analysis investor property loans generally carry a higher SatO, and also perform worse than owner-occupied properties; however, controlling for SatO (i.e., for a similar SatO level) investor property loans may perform better than owner occupied properties.

T) NUMBER OF BORROWERS (GSE ONLY)

The MILAN model adjusts the loan PD to distinguish loans backed by one borrower from loans backed by more than one borrower. Default risk is greater for single-borrower loans.

U) NUMBER OF UNITS (GSE ONLY)

The MILAN model adjusts the loan PD to distinguish loans backing one property unit from those with more than one property unit. Default risk is greater for loans backing multiple units.

V) ARM LOANS (PRIVATE LABEL ONLY)

The MILAN model adjusts PDs for loans that do not have a fixed interest rate. This adjustment will depend on the initial fixed-rate period of the loan to account for self-selection, meaning that the choice of a 3/1 hybrid rather than a 7/1 may be predictive of the borrower's risk profile, all else equal. Other features of the ARM loan, such as the reset period and any caps or floors in interest rate levels or changes, are incorporated into the modeling of the loan's interest rate and hence CLTV path.

W) GROSS MARGIN (PRIVATE LABEL ONLY)

The MILAN model increases the PD for higher ARM margins. The ARM margin is the amount the borrower must pay above its index rate for the adjustable-rate mortgage. Like SatO, the ARM margin correlates with borrower risk – higher the ARM margin, the higher the borrower risk.

X) CUMULATIVE CHANGE IN LOAN INTEREST RATE (PRIVATE LABEL ONLY)

The MILAN model adjusts the loan PD to reflect the (cumulative) change in the loan's interest rate since origination. This adjustment is in addition to any influence the loan's rate has on the path of CLTV and reflects the fact that if the loan's rate has increased (decreased) since origination, the borrower presumably is experiencing increased (decreased) payment pressure which may impact the propensity to default.

Step (3): Benchmark severity

The third step is calculating the expected loss severity in the event the borrower defaults, assuming that resolution takes the form of liquidation. The main drivers of severity are the property's value at liquidation, the securitized loan balance, the loan's interest rate, foreclosure costs, and the time to foreclosure.

In the Aaa scenario, the MILAN model incorporates an explicit scenario of house price depreciation (HPD). To determine expected loss severity, we first calculate the updated property value, by applying the HPD scenario to the updated property value at the time of analysis,[38] as Formula 3 shows. The HPD scenario in Formula 3 is the same scenario that we use in our PD analysis. It represents our assumption of how far the property value will fall between origination and liquidation.

FORMULA 3

$$PV_{Updated} = PV_{Time\ of\ Analysis} * (1\text{- HPD})$$

Where:

» $PV_{Updated}$ = Updated property value

» $PV_{Time\ of\ Analysis}$ = Property value at the time of analysis

Source: Moody's Investors Service

We then derive the unadjusted expected loss severity of a particular loan using Formula 4.

38 See the "House Price Changes" section above for an explanation of how we take into account changes in property value from loan origination to the time of analysis.

FORMULA 4

$$L_{Unadj} = Max(CB - \vartheta * PV_{Updated} + FC + VC*t + SA, 0)$$

Where:

- L_{Unadj} = Loss on loan, prior to adjustments for non-benchmark attributes
- CB = Loan balance at liquidation including unpaid interest obligations, reduced by servicer advancing of principal and/or interest, as needed
- ϑ = Gross recovery fraction of the property value
- $PV_{Updated}$ = Updated property value from Formula 3
- FC = Fixed foreclosure cost (for example, costs which do not depend on the time to liquidation)
- VC = Variable foreclosure costs (e.g., costs which do depend on the time to liquidation, such as taxes, maintenance and insurance)
- t = Foreclosure period in months
- SA = Cumulative servicer advancing of principal and/or interest, as needed

Source: Moody's Investors Service

HPD: The loan's loss severity depends on the property value at liquidation. HPD is the same value we use in our PD analysis.

Loan balance at liquidation: We model the loan balance at liquidation by assuming it follows scheduled amortization from its current balance, with appropriate adjustment for any servicer advancing of principal. To this we add any unpaid interest proceeds, with appropriate adjustment for any servicer advancing of interest.

Gross recovery fraction: The gross recovery fraction represents how much of the house value at liquidation will be recovered from the sale proceeds. This rate increases with the degree of leverage at default, but we cap it at 94% to reflect sales commissions. Making the gross recovery fraction positively related to leverage at default has the effect of reducing, relative to simply mechanical expectations, the sensitivity of loss to LTV. This observation partially reflects the adverse selection of borrowers with low LTV who ultimately default; because most borrowers who have significant equity in their properties will sell their homes before foreclosure, the ones who do go through the foreclosure process are more likely to do so because of idiosyncratic property-related risks. As a result, it is unlikely that their true LTV is as low (or that their property value is as high) as the model might suggest.

Fixed foreclosure costs: We estimate the fixed costs of the legal proceedings and auction sale, based on the borrower's geographic location. Our legal cost estimate is higher for judicial states[39] to account for the additional costs associated with required court proceedings.

Variable foreclosure costs: We estimate the variable costs of the foreclosure process, that is, those costs that increase with the time to foreclosure. Chief among these would be taxes, insurance and property maintenance.

Time to foreclosure: We use historical data to estimate the time to foreclosure and differentiate between states with judicial and non-judicial foreclosure processes. The time to foreclosure will typically be longer for loans to borrowers in judicial states than for loans to borrowers in non-judicial states.

[39] Judicial states are those states in the US where the foreclosure process is handled by the state's court system. The foreclosure process in those states takes longer than in non-judicial states where properties are foreclosed without court intervention.

Servicer advances: The servicer may, for a period of time, advance interest, principal, or both, as well as taxes, insurance premiums and miscellaneous administrative costs. We reflect such advances positively by reducing the effective loan balance at liquidation, but then we subtract those advance proceeds recovered from the property. Put simply, while the servicer may advance $1, it will then pay itself back $1 when the account is finally liquidated. As such, servicer advancing tends to have limited impact on final loss severity estimates.[40]

FICO: Recovery from the sale of the property is typically greater for borrowers who have higher FICO scores. This factor is explicitly incorporated into the GSE LGD model only because it was not significant in the private label dataset.

Liquidation vs. Short Sale Flag: The process used to dispose of a property, whether through a liquidation or short sale, has implications for both the recovery from the sale of the property and the foreclosure costs. Compared to properties disposed through short sale, those disposed through liquidation typically recover less due to the fire-sale nature of the transaction and typically have higher expenses due to the more complicated legal processes. This difference is explicitly accounted for in our GSE LGD model where we typically assume that each defaulted loan has a 67% probability of going through liquidation. This factor is explicitly incorporated only into the GSE LGD model because these data are only available in the GSE dataset. In the private label LGD model, the probability of a short sale is not modeled explicitly but rather factored in the overall recovery rate.

Step (4): Non-benchmark loan-level severity adjustments

Using Formula 5, the MILAN model makes additional adjustments to the loss severity if certain attributes differ from those of the benchmark loan. Specifically, occupancy and property type will result in changes to the amount of recovery proceeds. As with adjustments to PD, the value of these adjustments depends on the values of the other loan and property attributes; therefore, we cannot determine ex-ante the exact value of a penalty for a given loan. We can however determine the typical range for a penalty, available in the US parameter settings that can be found in Appendix 8.

A) OCCUPANCY TYPE

We raise the assumed loss severity for non-owner-occupied properties, such as second homes and investor properties, because they are usually not as well-maintained as owner-occupied homes.

B) PROPERTY TYPE

We raise the assumed loss severity for two-to-four family properties because they are typically less liquid and more difficult to value.

[40] The advancing of principal can reduce loss severity, all else equal, as it reduces the interest obligation of the loan, but this effect is usually small. By itself, advancing interest is assumed to net out, since every dollar advanced is simply recaptured upon liquidation. Advancing of principal and/or interest however affects the timing of cash flows, including the probability of making timely interest payments, and can therefore have an impact on the credit quality of the various RMBS tranches.

FORMULA 5

$$L_{Adj} = L_{Unadj} * OA * PA$$

Where:

» *OA* = Occupancy adjustment

» *PA* = Property type adjustment

Source: Moody's Investors Service

We may also selectively use the GSE model calculations to inform our adjustments for loan attributes that are exclusively incorporated in the GSE model when analyzing a non-GSE portfolio.

Step (5): Loan-level model-implied CE

After calculating the loan-level adjusted PD and severity in our stress scenario, we define the loan-level model-implied CE as their product, as in Formula 6. We might make further adjustments to this number to account for other loan-level attributes that we did not explicitly model as part of the PD and loss severity calculations (discussed in Step 6) and our review of origination quality or servicing arrangements (discussed in Step 7).

FORMULA 6

$$Loan\ CE = PD_{Adj} * L_{Adj}$$

Source: Moody's Investors Service

Step (6): Loan-level adjustments – other

Additional adjustments to the loan-level model-implied CE might sometimes be warranted for loans with risk attributes that the model does not fully capture. As further described below, when considering such adjustments, we evaluate the extent to which these risk attributes are present in the pool. In addition, specific underwriting requirements (such as income and asset verification) and originator practices (such as the method of calculating debt-to-income ratios) could differ by mortgage product. These considerations may be accounted for with loan-level adjustments. The additional adjustments covered in this step may have a positive or negative impact on the Portfolio EL and MILAN CE.

We review the following attributes to assess the need for additional adjustments.

A) DTI (PRIVATE LABEL LOANS ONLY)

The extent to which a borrower's income is sufficient to cover the mortgage payment, property taxes, living expenses and other debt obligations is a key determinant of a borrower's ability to repay the mortgage. Sufficiency of income is most typically measured as the ratio of total debt service to gross income (DTI). DTI is explicitly incorporated into the GSE PD model, and hence further adjustment is not typically needed. However, DTI is not part of the private label PD model due to the limited, and sometimes unreliable, way in which it was reported historically. Hence, we do not make an out-of-model adjustment if DTI is within the range that we typically observe in private label securitizations. Some loans with high DTIs might not necessarily be risky, because borrowers with higher loan balances could also have higher levels of disposable income for a given DTI. In addition, high levels of liquid reserves and other borrower attributes can offset the risk of a high DTI.

B) MORTGAGE INSURANCE

The benefit of mortgage insurance is a function of (i) the applicable insurance coverage criteria at the loan level; (ii) the proportion of MI claims for which the conditions of payment under the insurance policy are not satisfied (the rejection rate); and (iii) the insurer's rating. Based on these factors, we make adjustments to the pool-level loss scenarios. For more details, see Appendix 5.

C) BORROWERS WITH MULTIPLE MORTGAGED PROPERTIES (PRIVATE LABEL LOANS ONLY)

Borrowers with more than one mortgaged property could be more likely to default than borrowers with one property, especially in a distressed housing market. When a borrower has multiple properties, especially when one is an investment property, verifying occupancy status is more difficult. In addition, the borrower's DTI will depend partially on less stable sources of income than traditional wages, given the borrower's use of the rental income from the investment property or properties to qualify for the loan.

Many borrowers with multiple properties are not high risk; they could be wealthy borrowers with stable incomes that support debt payments on vacation properties, or successful landlords with significant levels of liquid reserves. We may evaluate loans to borrowers with multiple properties to determine if the transaction warrants additional adjustments.

D) LOAN PERFORMANCE

Cases in which a borrower is or was delinquent, or, to a lesser degree, in which a first payment has not yet become due, pose a greater risk of nonpayment than cases where the borrower has made timely initial payments. We may adjust loan-level CE if this risk is material.

E) ADVERSE CREDIT EVENTS

Often, originators have underwriting guidelines that require a period of time to elapse following a significant credit event, such as a foreclosure, bankruptcy or short sale, in order to qualify for a new loan. Some credit characteristics, such as FICO, reflect these credit events. However, borrowers with recent significant credit events could pose more risk. We may evaluate loans to borrowers with recent instances of these kinds of credit events on a case-by-case basis and may adjust the loan-level CE.

F) SELF-EMPLOYED BORROWERS (PRIVATE LABEL LOANS ONLY)

Self-employed borrowers typically have less stable incomes than wage earners, although a self-employed borrower is not always riskier than a wage earner. Given the volatility of their income, we assume higher losses for self-employed borrowers if their concentration in the pool is greater than the concentration observed in typical pools,[41] which would already be reflected in the historical data.

G) ORIGINATION CHANNEL (PRIVATE LABEL LOANS ONLY)

Loans originated through different origination channels often perform differently. Typically, loans originated through a broker or correspondent channel do not perform as well as loans originated through a retail channel, although performance will vary by originator. Origination channel is explicitly incorporated into our GSE PD model, however it is not a factor in the private label PD model. We may adjust the loan-level CE for loans originated through different origination channels depending on whether the originators have stronger or weaker controls over third-party origination channels, especially when an adjustment is supported by performance data.

H) LOANS TO FOREIGN NATIONALS

Loans to foreign nationals have different risks than loans to US citizens. Originator underwriting guidelines for programs that allow loans to foreign nationals typically have different requirements to address the unique risks of these loans. Since they can vary significantly from originator to originator, and ultimately may have a large impact on the PD, we evaluate loans to foreign nationals on a case-by-case basis and may adjust the loan-level CE.

[41] For private label pools, we typically apply a 10% adjustment to the Portfolio EL and a 20% adjustment to the MILAN CE on the portion of the loan balances from self-employed borrowers that exceeds 25%. If the proportion of self-employed borrower balances is not known, we would assume that all the borrowers in the pool are self-employed borrowers. Moreover, if the originator's underwriting guidelines for self-employed borrowers are looser than the typical guidelines we observe for these borrowers, we may apply an additional 10% adjustment to the entire proportion of self-employed loans.

I) SEASONED LOANS

We may perform additional analyses for transactions with a significant portion of loans that are heavily seasoned. These analyses could incorporate a review of additional data and adjustments to the way we consider certain loan attributes. For example, for very seasoned loans we typically account for the loans' performance history, recent updated FICO scores, valuations, or all three if available, and might make adjustments to penalties or benefits associated with loan-level attributes.

J) EVENT RISK

For a geographically concentrated portfolio, we could also consider unmitigated event risk in our analysis. For example, in the absence of earthquake or flood insurance, we might adjust the MILAN CE for portfolios that contain a significant proportion of loans in earthquake- or flood-prone areas.

K) MORTGAGE INSURANCE-LINKED NOTES

For transactions transferring mortgage insurance exposure, we will adjust both the probability of default and the loss severity on the assets. For probability of default, we will consider the timing of termination on mortgage insurance. In particular, we determine the forecast horizon in the PD model by the period MI is still in effect, i.e., the default projection for a loan stops once MI terminates. For loss severity, we will follow our approach to reduce loss severity when MI is present. The LGD in this case is determined by the claims amount eventually paid by the MI provider.[42]

These transactions are structured to default if the mortgage insurance provider stops making premium payments to the securitization, which could be the case if the provider is insolvent. Upon a default, the rated notes would be paid off from liquidating the collateral account, incurring no further collateral losses. From this perspective, and all else being equal, a weaker credit quality provider, who will be closer to insolvency, would benefit these transactions as compared to a stronger credit quality provider.[43] However, we expect that in practice the provider (or its regulator) would likely continue to make premium payments to the risk transfer transactions even in regulatory rehabilitation, to preserve the benefit of the insurance coverage that the transactions provide to the MI company. As a result, we typically assume more conservatively that the credit quality of the provider is very strong; to reflect this assumption, we enter a Aaa rating in our model as the provider rating.

L) MODIFIED LOANS

In calibrating the model, we treated modified loans as defaulted. When forecasting the liquidation probability for modified loans in a pool, however, we typically apply a multiplicative factor to the loan-level MILAN PD. Generally, we apply a 7x multiple to the PD for private label modified mortgage loans and an 8x multiple to the PD for GSE-eligible modified mortgage loans. This multiple is applied regardless of whether a mortgage loan was modified before or after deal closing.[44]

We may also qualitatively or quantitatively factor in the analysis of any other loan attribute that is not a model input.

Step (7): Loan-level adjustments – origination quality, servicing arrangement, third-party review and representations and warranties

Origination quality can also affect performance. Our adjustments typically range from a 10% reduction in loan-level model-implied CE for stronger origination platforms and processes, to a 50% increase in loan-

[42] For more information, see Appendix 5; however, note that our rejection rate assumptions would likely be different for MI-linked notes than for transactions where MI reduces pool losses.

[43] In our modeling, the LGD is determined by the claim amount paid by the MI provider, with a weaker MI provider expected to pay a lower claim amount than a stronger MI provider.

[44] In cases where the model adjusts the calibration factor due to performance that is significantly worse than expected, we will not apply a 7x or 8x multiple to the PD of loans modified after closing when calculating the Portfolio EL.

level model-implied CE for weaker origination processes. In certain instances, the adjustments could be larger. We may make additional adjustments to account for other aspects of a transaction that may impact performance, such as the servicing arrangement, independent third-party diligence report reviews, and representations and warranties. Some of these adjustments may apply at the transaction level as mentioned in Step 11.

Step (8): Final loan-level CE

Using Formula 7, we calculate the final loan-level CE as the product of the loan-level model-implied CE with the loan-level adjustments we calculated in Step 6 and Step 7.

FORMULA 7

$$Loan\ CE_{Adj} = Loan\ CE_{MI} * Loan\ Level\ Adjustments$$

Source: Moody's Investors Service

Step (9): Pre-Concentration MILAN CE

After calculating a final loan-level CE for all of the loans in the portfolio, the MILAN model calculates pre-concentration MILAN CE, which is simply the weighted average final loan-level CE, where the weights are based on each loan's share of the portfolio, as Formula 8 shows.

FORMULA 8

$$MILAN\ CE_{Pre\text{-}Conc} = (\Sigma Loan\ CE_{Adj} * Loan\ Balance)/Portfolio\ Balance$$

Source: Moody's Investors Service

Step (10): Concentration adjustment

To determine the MILAN CE, the MILAN framework takes into account the degree of both borrower and geographic concentration in the portfolio. High geographic concentrations are the result of large proportions of loans collateralized by properties in a particular postal code or MSA. High borrower concentration can be the result of a portfolio with a small number of loans or with loans with disproportionately large balances.

The MILAN CE increases with the degree of geographic concentration. High geographic concentration exposes a portfolio to the risk of higher losses if economic conditions in the concentration region deteriorate materially, which effectively increases the probability of high losses. We measure geographic concentration using the Herfindahl-Hirschman Index (HHI) for MSAs and postal codes.

Furthermore, we also increase the local house price decline for portfolios with an HHI by MSA of less than 30 MSAs. The house price decline will depend on the number of effective MSAs; the higher the concentration, the greater the local house price decline.

High borrower concentrations make portfolios more susceptible to idiosyncratic losses, which also increases the probability of high losses. The MILAN model increases CE with borrower concentration, whether that concentration is the result of a low number of borrowers or the presence of disproportionately large loans.

The MILAN model adjustments for high concentration are based on the effective number (measured by HHI) of borrowers (if less than 3,000), postal codes (if less than 3,000) and MSAs (if less than 60) represented in the portfolio and are applied as a multiple to the unadjusted portfolio CE or as higher local house price decline assumptions (if the effective number of MSAs is less than 30). The following are the formulas for these adjustments.

FORMULA 9

$$Concentration_{Borrower} = MILAN\ CE_{Pre\text{-}Conc}\ \text{^}(BA*(\ln(BC)-\ln(HHI(Borrower))))$$

FORMULA 10

$$Concentration_{PostalCode} = MILAN\ CE_{Pre\text{-}Conc}\ \text{^}(ZA*(\ln(ZC)-\ln(HHI(PostalCode))))$$

FORMULA 11

$$Concentration_{MSA} = MILAN\ CE_{Pre\text{-}Conc}\ \text{^}(MA*(\ln(MC)-\ln(HHI(MSA))))$$

FORMULA 12

$$MILAN\ CE_{Conc} = Concentration_{Borrower}*Concentration_{PostalCode}*Concentration_{MSA}$$

FORMULA 13

$$Local\ HPD = (0.60 + (\min(HHI(MSA),30)-1)*0.2897)/\min(HHI(MSA),30)$$

Where:

» *BA* = Adjustment factor for borrower concentration

» *ZA* = Adjustment factor for postal code concentration

» *MA* = Adjustment factor for MSA concentration

» *BC* = Effective borrower count for a diversified portfolio

» *ZC* = Effective postal code count for a diversified portfolio

» *MC* = Effective MSA count for a diversified portfolio

» $HHI(Borrower) = 1/\Sigma(BWm)^2$

» $HHI(PostalCode) = 1/\Sigma(ZWm)^2$

» $HHI(MSA) = 1/\Sigma(MWm)^2$

» BW_M = Weight of the total exposure to borrower *M* in the portfolio

» ZW_M = Weight of the total exposure to postal code *M* in the portfolio

» MW_M = Weight of the total exposure to MSA *M* in the portfolio

Source: Moody's Investors Service

Step (11): MILAN CE

We generally take into account additional qualitative factors, such as transaction governance and incentive alignment, that could result in further adjustments to the MILAN CE. Finally, the MILAN CE is subject to a floor equal to the portfolio-level expected loss multiplied by the Aaa multiple.

FORMULA 14

$$MILAN\ CE = Max(MILAN\ CE\ Floor,\ MILAN\ CE_{Conc})$$

Where:

» *MILAN CE Floor* = Portfolio-level expected loss multiplied by Aaa multiple

Source: Moody's Investors Service

Illustrative Example of MILAN CE Calculation

Exhibit 9 shows how we calculate the MILAN CE, using indicative values for the various adjustments. This is a simplified example and the values illustrate how we make the adjustments to the base PD and severity at the loan level and roll up to a portfolio-level MILAN CE.

EXHIBIT 9

Illustrative Example of MILAN CE Calculation

Step (1):	Benchmark PD	10%
Step (2):	Non-Benchmark PD Adjustments	
	Non-Benchmark Characteristics	**Non-Benchmark Characteristics Adjustments**
	DTI	1.20 (P1)
	Original Term to Maturity	1.00 (P2)
	Balloon Loan	1.00 (P3)
	Original Interest Rate	1.05 (P4)
	Prepayment Benchmark Rate Effective	1.00 (P5)
	ARM Loan	1.00 (P6)
	Initial Fixed-Rate Period	1.00 (P7)
	Gross Margin	1.00 (P8)
	Original Interest Only Term	1.10 (P9)
	Prepayment Penalty Total Term	1.00 (P10)
	Channel	1.20 (P11)
	Documentation	1.00 (P12)
	Occupancy Type	1.10 (P13)
	Property Type	1.08 (P14)
	Loan Purpose	1.00 (P15)
	Judicial	1.10 (P16)
	First Time Home Buyer	0.80 (P17)
	Borrower Count	0.85 (P18)
	Unit Count	1.00 (P19)
	House Value MSA	1.10 (P20)
	House Value US	1.10 (P21)
	Rate Spread	1.05 (P22)
	Seasoning	0.90 (P23)
	Loan Payment	0.95 (P24)
	Cumulative PD Adjustment[1]	1.605
	Adjusted PD[2]	**16.05%**

[1] Cumulative PD Adjustment = P1 x P2 x … x P24

[2] Adjusted PD = Benchmark PD x Cumulative PD Adjustment

Step (3):	Benchmark Severity	35%
Step (4):	Non-Benchmark Severity Adjustments	
	Non-Benchmark Characteristics	**Non-Benchmark Characteristics Adjustments**
	Occupancy	1.20 (S1)
	Property Type	1.05 (S2)
	Adjusted Severity[3]	**44.10%**
Step (5):	Loan-Level Model-Implied CE[4]	7.08%
Step (6):	Other Loan-Level Adjustments (not related to Origination Quality and Servicing Arrangements)	1.00
Step (7):	Origination Quality and Servicing Arrangement Adjustments	1.05
Step (8):	Adjusted Loan-Level CE[5]	7.43%
Step (9):	Pre-Concentration MILAN CE[6]	7.43%
Step (10):	Concentration Adjustment	1.30
Step (11):	MILAN CE[7]	9.66%

[3] Adjusted Severity = Benchmark Severity x S1 x S2

[4] Loan-Level Model-Implied CE = Adjusted PD x Adjusted Severity

[5] Adjusted Loan-Level CE = Loan-Level Model-Implied CE x Other Loan-Level Adjustments

[6] Pre-Concentration MILAN CE = weighted average Adjusted Loan-Level CE. Assuming that all loans in the pool have the same adjusted loan-level CE and same balance for this example.

[7] MILAN CE = Max (Pre-Concentration MILAN CE x Concentration Adjustment, Portfolio EL x multiple)

Source: Moody's Investors Service

Step (1): Benchmark PD

Benchmark PD is the default probability for a benchmark loan for a given CLTV and FICO for the life of the loan. In this example, it is 10%.

Step (2): Loan-level adjustments for borrower and loan attributes

We adjust the benchmark PD to account for non-benchmark loan attributes, applying each adjustment as a multiple. In this example, the loan has a number of non-benchmark loan attributes: DTI, original interest rate, an interest-only payment period, channel, occupancy, property type, judicial state, first-time home buyer, number of borrowers, value spread (US and MSA), credit spread at origination, seasoning and loan payment. The aggregate PD multiplier is 1.61. The adjusted PD in this example is 16.05%, which we calculate by multiplying the benchmark PD of 10% by the aggregate PD multiplier of 1.61.

Step (3): Benchmark severity

We calculate the benchmark severity as the excess, if any, of the loan balance over the recovery proceeds net of expenses. We calculate the net recovery proceeds by multiplying the property value at liquidation by the gross recovery fraction, minus the foreclosure costs and the carrying costs of the loan. In this example, the benchmark severity is 35%.

Step (4): Non-benchmark severity adjustments

We adjust the benchmark severity to account for non-benchmark attributes. In this example, the loan is not for an owner-occupied or a single-family home, which results in an aggregate severity multiplier of 1.26 to the benchmark severity. The adjusted severity in this example is 44.10%, which we calculate by multiplying the benchmark severity of 35% by the 1.26 aggregate severity multiplier for the non-benchmark characteristics.

Step (5): Loan-level model-implied CE

We calculate the loan-level model-implied CE as the product of the adjusted PD and the adjusted severity. In this example, the 16.05% adjusted PD multiplied by the 44.10% adjusted severity results in a loan-level model-implied CE of 7.08%.

Step (6): Other loan-level adjustments (not related to origination quality and servicing arrangements)

In this step, we apply any additional loan-level adjustments to account for other loan attributes that the model may not capture. The 1.00 multiple in this example indicates that we make no further adjustments.

Step (7): Origination quality and servicing arrangement adjustments

In this example, we make a 5% adjustment for origination quality and servicing arrangements, shown as a 1.05 multiple to the loan-level model-implied CE.

Step (8): Final loan-level CE

We calculate the adjusted loan-level CE as the product of the loan-level model-implied CE, the origination quality and servicing arrangement adjustments multiplier from Step 7, and the other loan-level adjustments multiplier from Step 6. In this example, we simply apply the 1.05 multiplier to the loan-level model-implied CE, resulting in an increase in loan-level CE to 7.43% from 7.08%.

Step (9): Pre-Concentration MILAN CE

The pre-concentration MILAN CE is the weighted average adjusted loan-level CE. In this example, we assume a portfolio of loans with the same adjusted loan-level CE, so the pre-concentration MILAN CE is the same as the adjusted loan-level CE.

Step (10): Concentration adjustment

The concentration adjustment results in a concentration-adjusted MILAN CE, which we calculate for the entire portfolio as a product of the pre-concentration MILAN CE, the borrower-level concentration adjustment, the postal code-level concentration adjustment and the MSA-level concentration adjustment. In the example, the concentration adjustment results in a 30% rate of increase to the pre-concentration MILAN CE of 7.43%. The concentration-adjusted MILAN CE is 9.66%.

Step (11): MILAN CE

We calculate the MILAN CE as the higher of the concentration-adjusted MILAN CE and the MILAN CE floor as determined by Portfolio EL multiple. We calculate the MILAN CE floor as the product of the Portfolio EL and the Aaa multiple. In this example, the MILAN CE floor does not affect the MILAN CE, and the result is a MILAN CE of 9.66%.

Appendix 2: Lognormal Distribution

We use the two outputs, Portfolio EL and MILAN CE, from our asset analysis to determine a collateral loss distribution. This distribution specifies the probability of each potential future loss scenario for the portfolio. For RMBS portfolios, we typically assume that the collateral loss distribution is lognormal and use two parameters to determine it:

» **Portfolio EL**: assumed to be the median central tendency of the lognormal loss distribution.

» **MILAN CE**: defined as the subordination of a theoretical synthetic senior tranche targeting a Aaa (sf) rating.

We assume that the loss distribution is censored at the lesser of 100% and twice the MILAN CE. We then find the lognormal distribution which satisfies the following two conditions: (i) its median is equal to the Portfolio EL, and (ii) the expected loss for a senior synthetic tranche that attaches at the MILAN CE point (and in consideration of the censoring described above) is equal to the loss associated with the Aaa (sf) level from our Idealized Expected Loss table evaluated at the appropriate horizon.

The horizon used for calibrating the loss distribution[45] is generally given by the minimum of the following:

» A maximum time horizon set at 30 years.

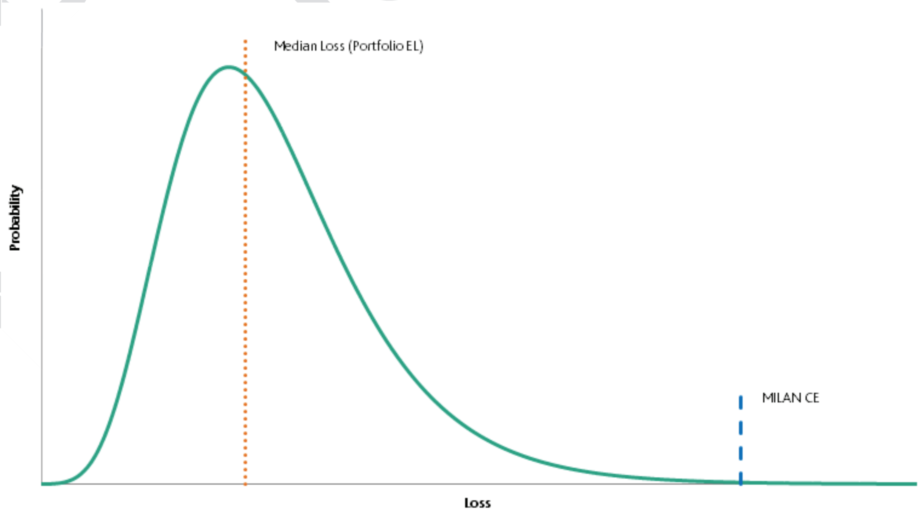
» The remaining life of the transaction (determined using the legal final maturity of the bond with the longest life).

» The weighted average life of the pool assuming no collateral defaults and a 5% annual prepayment rate.[46]

Note that when analyzing portfolios which benefit from mortgage insurance or government guarantee, or which may be synthetic in nature with pre-defined loss given default rates, the final loss distribution may no longer be strictly lognormal.

EXHIBIT 10

General Shape of the Lognormal Loss Distribution



Source: Moody's Investors Service

[45] If the deal has multiple pools, we will use the weighted average of the horizons calculated for each pool.

[46] For defaulted loans, this item is calculated using the weighted average liquidation duration in the baseline scenario.

Appendix 3: Cash Flow Analysis

Once we have completed our asset analysis, we analyze the transaction structure, cash flow waterfall and level of credit protection available to the relevant tranches to determine their ratings. The primary input for the cash flow analysis is the collateral loss distribution (decomposed into its constituent PD and LGD distributions) as described above. We generally perform a cash flow analysis to assess a transaction's structure. The cash flow analysis captures a number of nuances in the structure, such as shifting interest waterfall, excess spread, triggers, and loss allocation, all of which influence the cash flows (and losses) to the tranches.

We use a discrete number of portfolio loss scenarios defined by the collateral loss distribution as inputs to our cash flow model, along with different prepayment and loss timing assumptions, to determine the sensitivity of our ratings to various scenarios. We typically use 12 combinations of loss and principal prepayment timings for each loss point. The scenarios combine three loss-timing curves and four prepayment curves. Depending on the circumstances specific to a particular transaction, we will run more or fewer scenarios or even scenarios different from those we describe below.

In transactions that are not fully hedged (i.e., floating-rate liabilities backed by fixed-rate assets or fixed-rate liabilities backed by floating-rate assets), and where the notes are not subject to a net WAC cap, we generally stress the interest payable on the notes or haircut the interest payable by the assets.

Loss Timing

Typically, for each loss point we input in the cash flow model, we apply the three loss-timing scenarios in Exhibit 11: front-ended, base and back-ended. These curves represent the relative temporal distribution of the loss under that scenario.

EXHIBIT 11

Loss Timing Assumptions

% of total losses incurred, by year since issuance

Year	Front-Ended	Base	Back-Ended
1	8%	3%	0%
2	35%	20%	4%
3	29%	25%	22%
4	15%	20%	25%
5	7%	15%	18%
6	4%	9%	13%
7	1%	5%	11%
8	1%	3%	7%
Total	100%	100%	100%

Source: Moody's Investors Service

Prepayment Rates

We typically run multiple prepayment scenarios to simulate the potential timing of realized prepayments. First, we determine a base case prepayment rate for the transaction which we apply for the first year and then may vary over the life of the deal. Exhibit 12 shows the four prepayment timing curves for a base case prepayment rate of 5%. We model incremental yearly changes in prepayment rates as even monthly increases throughout the earlier year. We combine each of the four prepayment timing curves with the three loss-timing scenarios in Exhibit 11 to generate 12 stress scenarios.

EXHIBIT 12
Examples of Prepayment Timing Curves

	5% Prepayment Rate				25% Prepayment Rate			
Year	Back	Flat	Drop	Climb	Back	Flat	Drop	Climb
1	5%	5%	5%	5%	23%	25%	19%	25%
2	4%	5%	3%	5%	18%	25%	13%	27%
3	3%	5%	3%	6%	15%	25%	13%	30%
4	3%	5%	3%	6%	11%	25%	13%	32%
5	2%	5%	3%	7%	8%	25%	13%	33%
6	2%	5%	3%	7%	10%	25%	13%	33%
7	3%	5%	3%	7%	13%	25%	13%	33%
8	3%	5%	3%	7%	14%	25%	13%	33%
9	3%	5%	3%	7%	17%	25%	13%	33%
10	3%	5%	3%	7%	17%	25%	13%	33%

Source: Moody's Investors Service

We can replace or supplement these standardized scenarios with other scenarios more appropriate for stress-testing a given deal or the same deal over time in a changing environment or when performance information indicates. For instance, we might stress a front-pay bond, which is a bond that usually receives principal payments ahead of other classes and hence is likely to amortize faster in a high prepayment environment, with low prepayment assumptions and front-ended loss timing. Similarly, we might stress a last-pay bond, which receives principal after all the other bonds have received their principal and have declined to zero, with lower prepayment assumptions and back-ended loss timing.

Excess Spread

Excess spread is the difference between the interest paid on the mortgage loans and the sum of (1) the interest on the bonds and (2) the fees paid ahead of interest in the transaction waterfall. When excess spread is a form of credit enhancement, it can provide a significant amount of credit protection to investors. However, the amount of protection actually provided by excess spread will depend on four main factors:

1) The amount by which the average interest rate on the mortgage loans in the pool could decrease over the life of the securitization, which we refer to as WAC deterioration or yield compression. This compression might result from either (i) high-yielding mortgage loans prepaying or defaulting at a faster pace than other mortgage loans; or (ii) modifications of loan interest rates lowering the average rate.

2) An interest rate mismatch (e.g., fixed to floating) between assets and liabilities could reduce the amount of excess spread in the transaction in the event that interest rates move in a disadvantageous direction.

3) The weighted average life of the pool which depends on the speed with which mortgage loans prepay or default during the life of the securitization.

4) The amount of excess spread that "leaks out" of the transaction before it is needed to protect investors. The risk of leakage is typically highest in the early months of a transaction when losses are relatively low, and this risk is dependent upon the structure of the transaction.

We typically model the first two factors by applying a haircut, generally in the 15% to 30% range, to the weighted average interest rate of the mortgage loans in the pool to reflect that the loans with the highest interest rates are likely to prepay fastest and that loan modifications tend to lower the weighted average interest rate of the remaining loans. We use this calculated lower interest rate in our cash flow modeling. The exact mortgage-rate haircut is decided based upon the dispersion of interest rates for the collateral and the extent of interest rate mismatch. In certain cases, a haircut outside of this 15% to 30% range may be appropriate if there is excessive fixed-to-floating interest rate mismatch or other collateral or structural risks that could reduce the amount of excess spread available to cover losses.

We model the effects of the last two factors through the assumed prepayment rate, default and prepayment timing curves and the modeling of cash flows. For transactions with excess spread, we typically set the base case prepayment rate to a level in the 20% to 25% range of the pool balance per year. Our specific prepayment assumptions for a particular transaction are decided based upon historical data, pool characteristics and whether mortgage loans have prepayment penalties.

Rating Committee Considerations

The model generates cash flow and losses for the relevant tranche in a variety of scenarios. Rating committees review the model outputs which are based on our Idealized Expected Loss table and consider the dispersion of model outputs in various scenarios. If the model outputs include no more than two different ratings and the ratings are not more than one notch apart, then rating committees typically consider the mode of the model outputs. If the outputs show a tie, then rating committees commonly consider the lower of the two outputs. Rating committees assess all other model outputs on a case-by-case basis.

For transactions with stop-advance features (discussed under "Liquidity Analysis" below) committees may overweight the output of the back-ended loss curve.

Model outputs are one factor considered by rating committees which may make qualitative adjustments to the outputs when merited. In addition, rating committees may make further quantitative adjustments to the inputs of the models to test sensitivity and validate the results.

Liquidity Analysis

Most US RMBS transactions incorporate advancing mechanisms that typically mitigate liquidity risk. In the absence of adequate advancing arrangements or for pre-funded deals, we evaluate structural features that address timely payment of interest and principal such as reserve funds or liquidity facilities.

For transactions in which servicers advance on delinquent mortgage loans up to a limited number of days of delinquency (stop-advance features), we assess the cash flow impact to the relevant tranches based on the allocation of cash flows and reimbursement mechanism in the transaction structure. We may stress the implied level and timing of delinquencies in the analysis to assess any shortfall risk.

Appendix 4: US RMBS Data Quality Evaluation Guidelines

A key element of our analysis of an RMBS security is an evaluation of the mortgage loan's characteristics. In assessing those characteristics, we typically use data from the originator or other relevant transaction parties. Consequently, our assessment depends on the extent to which the data and the process used to collect the data are likely to provide an accurate representation of the loan characteristics.

As a part of our data quality evaluation, we generally consider the following four elements at the time of initial ratings:

» **Alignment of interest**. We evaluate the mechanism through which, and the extent to which, the issuer retains credit risk in the transaction. This analysis qualitatively informs us about how strongly aligned the issuer's and investors' interests are with respect to the performance of the loans and could influence how we evaluate the quality of the data.

» **Origination Quality**. We qualitatively evaluate an originator's underwriting and loan origination practices and an aggregator's loan acquisition practices.

» **Independent third-party review (TPR)**. A pre-securitization TPR of loan data in a transaction speaks to the reliability of the data we use in our analysis and informs our assessment of the loans' range of projected credit performance. We also use TPR results to identify parameters for sensitivity analysis that we use to determine the impact of any change in those loan attributes on the transaction's performance.

» **Representations and warranties (R&W) framework**. Our analysis of a transaction's R&W framework includes an evaluation of the scope of the R&Ws, their enforcement mechanisms, and the financial strength of the entity that provides them. Our evaluation of the R&W framework qualitatively informs us of how strongly aligned the issuer's and investors' interests are and could influence our evaluation of data quality. We examine enforcement mechanisms such as breach review triggers and post-securitization TPRs for breaches of representations and warranties, because they can enhance the value of R&Ws by increasing the R&W provider's accountability and transparency.

We evaluate the impact of all four of these factors collectively on the ratings in conjunction with each transaction's specific details and results of alternative relevant scenario analysis. In some cases, the strengths of some of the factors can mitigate weaknesses in others.

For RMBS surveillance, we start with the results of the data quality evaluation we perform to initially rate the transaction and then utilize the performance information we receive from the servicer or trustee over time. Typically, we consider the quality of the servicer or trustee reports adequate when the servicer has attested to their accuracy for regulatory purposes. Over time, a loan's actual performance becomes a more important indicator of future performance than any of the factors we initially assessed when we rated the transaction.

Alignment of Interest

An originator or aggregator is more likely to provide high-quality data if it has incentives to do so. To determine its incentives, we generally consider its business model. An originator that retains the credit exposure to its own originations will place a higher value on obtaining the high quality, reliable data needed to accurately assess the credit risk it carries on its balance sheet. Therefore, an originator that randomly selects loans from its portfolio for securitization while keeping a significant portion of its loans on its balance sheet will likely have better data than an aggregator that sells all of the loans it acquires and retains none of the credit risk. Similarly, an originator or aggregator that retains an economic interest throughout the life of a transaction will have a greater incentive to ensure that its loan data are reliable. In our view, a strong alignment of interest is a potential mitigant to weaknesses in other data quality factors.

Origination Quality

We generally assess originators and aggregators whose loans constitute more than 10% of an RMBS portfolio, identifying any business strategies, policies, procedures, and underwriting guidelines that could affect their loans' performance. We might make this assessment in a single deal as a part of relevant transaction analysis or use findings from our previously performed originator (or aggregator) review. For originators that contribute 10% or less to the portfolio, we generally gauge the quality and reliability of the loan data through TPRs and the aggregator underwriting guidelines, criteria and processes. Under certain circumstances, we also review the historical loan-level performance of originators that contribute less than 10% of the loans in the portfolio.

Our review of originators and aggregators includes a review of the following components:

» **Performance**: We review the performance data the originator or aggregator provides, to assess how their loans will perform in comparison with peers.

» **Ability**: We review originators' and aggregators' business strategies and origination or acquisition practices with reference to how they evaluate a borrower's ability and willingness to repay the loan, and assess the collateral value.

» **Stability**: We review originators' and aggregators' finances and operations.

When assessing these components we typically focus on following sub-components:

» loan origination and acquisition channels

» underwriting and/or acquisition guidelines

» property valuation procedures

» closing and post-closing activities

» third-party originator (brokers, correspondents and other originators) management

» credit risk management

» quality control and audit

» regulatory and compliance oversight

Analytical Impact of Origination Quality

Although we expect to assess most origination platforms as credit neutral for a given transaction, the originator's quality adjustment generally ranges from -10% to 50%. A negative adjustment reduces the loan-level model-implied CE, while a positive adjustment increases loan-level model-implied CE. We may further adjust the originator's adjustment, particularly if our evaluation is negative and we believe that the originator's or aggregator's policies, processes and practices will have a greater impact on the performance of its loans. If our review reveals serious deficiencies, we could decide to cap the ratings at a particular level or not to rate a transaction.

Appendix 5: Mortgage Insurance

This appendix describes our approach to analyzing mortgage insurance purchased by borrowers[47] or mortgage lenders.[48] Both BPMI and LPMI usually cover losses only on a portion of the loan. The key difference between the two types of insurance is that LPMI cannot be terminated during the life of the loan, while BPMI usually can be terminated when the LTV falls below a certain level.

The benefit of mortgage insurance (MI benefit) is a function of (1) the applicable Insurance Coverage Criteria at the loan level; (2) the proportion of insured losses for which the conditions of payment under the insurance policy are not satisfied (the rejection rate); and (3) the insurer's rating and/or strength of the backstop, if any. Based on these factors, we determine the maximum insurance payout and apply it in the severity calculation to make adjustments to the pool-level loss scenarios, as further described below.

Insurance Coverage Criteria

When mortgage insurance covers some but not all loans in the pool or the insurance policy contains coverage criteria that limit the claim amount to a certain balance and costs to a predetermined percentage, we calculate the insured losses on a loan-by-loan basis in consideration of the applicable criteria. We then aggregate the insured losses for all loans that benefit from MI from the respective insurance company, for each loss scenario.

Rejection Rates

Our rejection rate assumptions are estimates of insured losses for which the insurer is not required to make a payment,[49] expressed as a percentage of total insured losses. Using the rejection rates, we adjust the insured losses at the pool level for each loss scenario to obtain the non-rejected insured losses. Our rejection rate assumptions depend on the applicable loss scenario and whether there is a GSE backstop.[50] Our rejection rate assumptions also reflect improvements in mortgage insurance practices such as strong loan-level due diligence we have observed since the 2007-2009 financial crisis.

We expect GSE master policies with standards of proof for fraud-related rescissions, time limits and other restrictions by which insurers can claim negligent underwriting, and clearer procedures for submitting claims to result in lower rejection rates than have been observed during recent periods of stress.

In transactions that do not benefit from the GSE backstop, we determine rejection rates on a case-by-case basis taking into account, among others, the following factors:

Historical rejection rate: Data on historical rescissions, curtailments, and denial of claims provide an important starting point to our assumptions and offer insights into an individual lender's underwriting controls[51] and an insurer's approach to handling claims. We stress historical post-crisis rejection rates to account for potential increases during recession scenarios. We may assume a higher rejection rate when we have limited historical data. In addition, we may adjust the rejection rate over time in response to observed performance. In setting our assumptions, we also consider our ability to monitor the rejection rate, and we may assume a higher rejection rate when the quality of ongoing reporting is weaker.

[47] Borrower paid MI (BPMI).

[48] Lender paid MI (LPMI).

[49] We define rejection rate broadly to include rescissions, curtailments, and denial of claims.

[50] A GSE backstop is an agreement by which Fannie Mae or Freddie Mac covenant to cover losses on most types of rejected insurance claims, including claims that (i) the MI provider is unable to honor due to insolvency or (ii) are rejected by reason of deficient underwriting. These backstops have certain limits including scenarios in which seller or servicer is solvent but the GSEs are unable to enforce the seller's or servicer's repurchase or make-whole obligations.

[51] Throughout this section, where we refer to lender we would apply similar considerations to the aggregator that is sponsoring the transaction if applicable.

Contractual conditions of payment: We review the conditions of payment in the insurance master policy. In general, we assume higher rejection rates for policies with conditions of payment that are relatively hard to satisfy and lower rejection rates if loans are subject to rescission relief[52] or transactions include a backstop mechanism.

Underwriting: Where the conditions of payment include underwriting criteria, we review the underwriting arrangements for the securitized mortgage loans and the lender's underwriting standards. We generally apply lower rejection rates if mortgage insurers review all information necessary to underwrite the loan, such as income verifications, valuations, and credit bureau checks. We also assume lower rejection rates if the underwriting process is reviewed by an independent party, since it substantially reduces the risk of claim rejection resulting from irregularities in underwriting standards.

Alignment of interest: We generally apply higher rejection rates if the lender has a relatively limited interest in loan performance and is consequently less incentivized to comply with insurance conditions of payment.

Third-party oversight: We may assume lower rejection rates if there is an independent asset manager or a deal agent that can oversee the servicer's MI claims filing process for timeliness, accuracy and compliance with the insurance policy.

Representations and warranties: We may assume lower rejection rates for transactions depending on the quality of the representations and warranties provided by the lender regarding the compliance with insurance conditions of payment. We will consider giving benefit to representations and warranties if:

» they are tightly construed.

» adequate and timely indemnities are in place in case of any loss to the transaction caused by a breach of representations and warranties.

» We would also consider the credit quality of the entity that is providing representations and warranties.

Exhibit 13 below shows our typical rejection rate assumptions.[53] The range of assumptions for transactions that do not benefit from the GSE backstop reflects the case-by-case considerations described above. Our baseline assumption for these transactions would more closely reflect actual observed rejection rates, generally with a floor of 1%.

EXHIBIT 13

Typical Rejection Rate Assumptions under the US MILAN Framework

GSE Backstop?	Aaa Assumption	Baseline Assumption
No	5%-20%	1%-5%
Yes	1%	0%

Source: Moody's Investors Service

[52] Contractual provisions under which an insurer waives it rights to rescind coverage on a mortgage.

[53] Our rejection rate assumptions would likely be different for MI-linked notes than for transactions where MI reduces pool losses (see Appendix 1).

Maximum Insurance Payout and Allocation

The maximum insurance payout (MIP) is determined using the insurer's rating. We determine the MIP at the pool level for each mortgage insurer such that the expected loss on non-rejected insured losses equals the Idealized Expected Loss implied by the insurer's rating.[54]

For example, if the insurer's rating is Baa2 and the weighted average life of the insured pool of mortgage loans is 10 years which corresponds to an expected loss of 1.98%,[55] we calculate MIP so that the expected loss on the non-rejected insured losses of that pool after MIP is depleted would correspond to 1.98%.

In other words, we calculate the non-rejected insured losses in each modeled loss scenario, and subtract MIP from each loss scenario, such that the expected value of that new loss distribution equals 1.98%. We determine MIP through an iterative process to achieve 1.98% expected loss on the new loss distribution.

After we determine MIP, we calculate the claims paid, i.e., the minimum of the non-rejected insured losses and MIP; the loss after accounting for the MI benefit is the difference between the loss before MI and the claims paid. [56]

Data

In assessing MI benefit, we typically use data provided by the sponsor of the transaction. As part of our assessment, we evaluate the quality of this data and based on that, we may adjust our modeling inputs or results. Therefore, our assessment of the MI benefit depends on the extent to which the data are likely to provide an accurate representation of the insurance coverage. In general, the less reliable the data, the more conservative are our assumptions.

54 The insurance rating is generally the Insurance Financial Strength Rating (IFSR). For more information, see the description of Insurance Financial Strength Rating in *Rating Symbols and Definitions*. A link can be found in the "Moody's Related Publications" section. If a rating is not available, we may use a credit estimate instead. No benefit will be given to MI providers that do not have a rating or a credit estimate.

55 For more information, see the discussion of Idealized Probabilities of Default and Expected Losses in *Rating Symbols and Definitions.* A link can be found in the "Moody's Related Publications" section.

56 We assume that mortgage insurance does not affect borrower behavior, therefore it does not change the default distribution.

Appendix 6: Considerations for Mortgage Loans with Alternative Documentation

The purpose of this appendix is to provide more information on how we view mortgage loans with alternative documentation.[57] The primary decision point for loans with alternative documentation is whether to classify such mortgage loans as partial or full documentation loans in the US MILAN model. For mortgage loans with less than 24 months of full documentation – for example, originator documentation approaches that rely on bank statements, asset qualifier/asset depletion and debt service coverage ratios (DSCRs) – documentation may be considered full or partial.

The categorization of mortgage loans as partial or full documentation depends upon a review of the originator's underwriting guidelines and documentation practices. In certain cases, we may apply additional qualitative adjustments for mortgage loans with alternative documentation. Below, we provide an overview of factors that we would consider.

Certain underwriting programs may raise risks under the Ability-to-Repay (ATR) rule, which requires lenders to verify income, assets, employment and debt using reliable third-party records. For example, if originators rely upon borrower-prepared profit and loss (P&L) statements to support income, this may create potential ATR non-compliance risks and raise the risk of fraud. We analyze these kinds of issues on a case-by-case basis, and may apply adjustments to our loss expectations, cap the ratings or decline to rate the transaction.

Bank Statement Loans

We classify bank statement loans as either partial or full documentation based on a wholistic review of the originator's documentation guidelines. Typical considerations in assessing the soundness of an originator's documentation practices include the number of months of bank statements required and the overall quality of underwriting. When evaluating underwriting quality, we assess the rigor used in calculating income and the utilization of business or personal bank statements.

Income documentation based upon 24 months of bank statements provides more assurance that the income is sustainable and less subject to manipulation than documentation based upon 12 months of bank statements. However, when evaluating documentation based on bank statements, the time frame of the statements being provided is only one factor that we consider.

There is a certain degree of subjectivity involved in the underwriting process, as the underwriter often checks bank statements for signs of fraud, trends of deposits being less than withdrawals, or declining income. As such, we consider underwriter training, experience, turnover, oversight and compensation structure when evaluating a bank statement program.

We view income calculated based on expense ratios as less precise than a direct calculation of borrower income. If an expense ratio is used, we consider the supporting data. Expense ratios that are tailored to the borrower's industry and geographic location based upon empirical evidence are stronger than simple expense ratios based upon broad assumptions and applied to all borrowers. The latter may increase the likelihood that the borrower will be unable to repay the loan.

Asset Depletion and Asset Qualifier Loans

Asset depletion loans are mortgage loans in which the assumed interest and amortization of a borrower's assets are used to reduce a borrower's DTI ratio and help the borrower qualify for the loan. Asset qualifier loans are mortgage loans in which the borrower's assets are large enough to enable the borrower to qualify for the loan without any consideration of the borrower's income. Asset depletion and asset qualifier loans

[57] Alternative documentation refers to documentation other than the one to two years of income verification, such as W-2s and tax returns, generally acceptable to the GSEs, for purposes of demonstrating the borrower's ability to repay.

typically represent a small portion of securitization pools and, in such cases, we typically treat them as partial documentation loans without further adjustments. However, for pools with a large portion of asset depletion or asset qualifier loans, we evaluate the interest rate assumptions, haircuts to asset values, and details of calculations to determine if the mortgage loans should be treated as partial or full documentation and whether additional adjustments are warranted.

DSCR Loans

DSCR loans are investment property mortgage loans where the originator utilizes the property's DSCR to underwrite the loan rather than the borrower's DTI or residual income. Because DSCR loans are made on investment properties, they are exempt from the ATR rules. We typically classify a DSCR loan as a partial documentation loan in our US MILAN model. For investor loans, DSCRs may be a more indicative metric of future loan performance than DTI ratios, which are more applicable to owner-occupied loans. Even borrowers in a weak financial position may selectively avoid default on a high-yielding and cash-flowing investment property. Nevertheless, borrowers with strong income profiles have more capacity to pay their mortgage during vacancy periods and make necessary improvements and repairs.

We may consider additional qualitative adjustments to our Portfolio EL and MILAN CE in cases where material percentages of the pool have low DSCRs or no borrower income documentation, where the underwriting guidelines have weak standards for calculating DSCR or allow for significant risk layering, or where there are other origination issues.

Other Forms of Alternative Documentation

We may view other forms of income documentation, such as verification of employment (VOE), less than 12 months of bank statements, and certified public accountant (CPA) profit and loss (P&L) statements as partial or full in our US MILAN model and may apply qualitative adjustments for such mortgage loans.

Appendix 7: Warehouse RMBS Transactions

Portfolio Analysis

For warehouse RMBS transactions, we typically model the Portfolio EL and MILAN CE by using a hypothetical adverse portfolio constructed by considering a transaction's eligibility criteria for the mortgage loan portfolio. When generating an adverse portfolio, we typically (1) assume an adverse numerical value from the criteria range for each loan characteristic (for example, highest allowable LTV ratios, lowest allowable FICO scores), (2) use risk layering for the mortgage loans within the eligibility criteria (for example, loans with the highest LTV ratio have also the lowest FICO score), and (3) apply the eligibility criteria restrictions such as the weighted average LTV ratio or FICO score, generally applying a barbell distribution (for example, loans with highly adverse characteristics combined with loans with benign characteristics to arrive at the weighted average, rather than a pool of loans all exhibiting characteristics at the weighted average value). Depending on the eligibility criteria, we may apply additional constraints when we construct a hypothetical portfolio.

Our Portfolio EL and MILAN CE reflect the portfolio's ultimate recovery and assume that the transaction will become a static pool following a sponsor default.

Other Considerations

When assessing warehouse RMBS transactions, we consider governance aspects regarding the transaction and sponsor, such as responsibilities and experience of transaction parties, operational capabilities of sponsors, the amount of time loans may remain in the warehouse facility (dwell time) and the allowable amount of seasoning for loans eligible for the warehouse. We also review the transaction structures to evaluate additional risks.

Analysis of Wet Loans

Wet loans are newly originated loans (figuratively, the ink on the signed pages is not yet dry) that a trust acquires as part of a warehouse RMBS transaction before the custodian has received the key collateral documents, such as the mortgage note. The trust is not fully collateralized until it receives these documents. If the documents do not arrive and the sponsor defaults on its obligation to make the trust whole for the resulting ineligible collateral, the trust could incur significant losses.

Foundational Structural Protections

When analyzing warehouse RMBS transactions with wet loans, we will look for the following foundational structural protections, or their equivalents, to be included in the transaction:

EXHIBIT 14

Foundational Structural Protections

	Protections	Parameters
1	Original revolving term	No longer than three years.
2	Maximum percentage of wet loans	Not exceeding 50% of the portfolio balance.
3	Time to deliver collateral documentation	Within 10 business days, after which, if not delivered, the loan becomes ineligible, its borrowing base value becomes zero, and the sponsor must deposit additional collateral if the required collateralization level is not met.
4	Financial covenants for the sponsor	Tangible net worth, liquidity, and debt-to-net worth consistent with those in market-standard bank warehouse facilities, breach of which would stop the warehouse RMBS transaction from funding new loans (not needed if 6(c) is present).
5	Closing protection letters or release letters	If the warehouse RMBS transaction provides funding for the closing of certain loans, the loan files should contain closing protection letters, or other equivalent protection, prior to funding. For loans that the warehouse RMBS transaction is acquiring from another warehouse lender, the transaction documents should require a release from that warehouse lender in connection with the funding, or other equivalent protection.
6	One of the following protections or an equivalent structural feature are present in a transaction:	
	a)	Wire instructions and warehouse bank funding recipients are set at closing, and changes require sign-off from a verification agent listed as a party to the warehouse RMBS transaction.
	b)	An independent fraud protection vendor approves wire instructions and is a transaction party, or a transaction party checks before funding that the fraud vendor has approved the wire instructions, or the transaction includes an equivalent review from an independent third party.
	c)	An investment-grade sponsor or guarantor is obligated to buy ineligible wet loans out of the trust, and the transaction includes a trigger to stop funding wet loans when the entity's rating falls below a Baa3 trigger. In the absence of such a provision, the sponsor's or guarantor's rating and overall credit profile must be significantly better than the trigger threshold, such that it is highly unlikely that the trigger is breached over the remaining term of the transaction.

Source: Moody's Investors Service

If certain of these structural protections are not present, we may consider compensating factors that provide an equivalent degree of protection on a case-by-case basis.

Rating Caps and Stress Scenarios

We apply the following rating caps and stresses when we assign and monitor ratings on warehouse RMBS that include wet loans:

EXHIBIT 15

Rating Caps and Stress Scenarios

Protections	Criteria	Rating Caps/Stress Scenario
Weak	Fails to include all of the foundational structural protections or their equivalents	May either give no credit to wet loans portion of the portfolio when deriving the MILAN CE or base the rating of the securities on the sponsor's or guarantor's rating.
Moderate	Includes foundational structural protections 1 through 5 or their equivalents and either 6(a) or 6(b) or its equivalent (see Exhibit 14)	(a) If a security has less hard credit enhancement* than the maximum wet loan portion, then the maximum achievable rating for that security is Aa3**; and (b) if the MILAN CE is lower than the maximum wet loan portion, we adjust the MILAN CE so that it equals the maximum wet loan portion. We do not adjust the Portfolio EL. In addition, we may apply alternative stresses or thresholds for rating caps in warehouse RMBS transactions with atypical structural features regarding the priority of payments, excess spread, or otherwise.
Strong	Includes foundational structural protections 1 through 5 (see Exhibit 14) or equivalents and an investment-grade sponsor or wet loan guarantor or equivalent (see 6(c) of Exhibit 14) and either: (1) there is a wet loan cut-off trigger or equivalent at the loss of Baa3 rating (or the entity's rating and the credit profile is significantly better than the trigger such that it is highly unlikely to breach the trigger over the remaining term), or (2) the transaction structure also includes foundational structural protection 6(a) or 6(b) or its equivalent (see Exhibit 14).	Rating caps and stress scenarios described in "Weak" and "Moderate" above are not applied.

* Hard credit enhancement includes subordination, reserve funds, and over-collateralization but excludes excess spread.

** A maximum achievable rating of Aa2 could also be possible when the structural protections are stronger than those in 6(a) and 6(b) in Exhibit 14. For example, a Aa2 rating would be possible if a transaction included the protections in 6(b) and also included a provision that reduces the risk of fraud by restricting the maximum percentage or amount that can be wired to any one particular account in a period.

Source: Moody's Investors Service

In addition to considering these structural protections, we also evaluate the sufficiency of the sponsor's overall operational controls for funding loans that will enter the warehouse facility, including controls for funding wet loans.

Monitoring

We periodically review relevant information such as the portfolio composition and performance, and ratings of relevant transaction parties, if appropriate. Typically, we do not re-run the model if the characteristics of the actual pool are within those of the adverse portfolio that we create at transaction closing. However, we would re-run the model if the actual portfolio begins to reflect the characteristics of the adverse portfolio. We also consider the length of the remaining revolving term (for example, one year or less) and the collateral characteristics of loans funded through the warehouse relative to the adverse pool, which may be mitigating factors

Appendix 8: US Parameter Settings

Government-Sponsored Enterprise Parameter Settings

The file contains: (i) assumptions used by the collateral analysis model to analyze GSE eligible fixed-rate loans, (ii) examples of benchmark PD for a loan given different values of borrower's FICO score and the borrower's CLTV and (iii) an illustration of penalty ranges that show how the benchmark PD for a loan might be impacted by non-benchmark loan attributes

Private Label Parameter Settings

The file contains: (i) assumptions used by the collateral analysis model to analyze private label first-lien mortgage loans, (ii) examples of the benchmark PD for a loan given different values of borrower's FICO score and the borrower's CLTV and (iii) an illustration of penalty ranges that show how the benchmark PD for a loan might be impacted by non-benchmark loan attributes.

Moody's Related Publications

Credit ratings are primarily determined through the application of sector credit rating methodologies. Certain broad methodological considerations (described in one or more cross-sector rating methodologies) may also be relevant to the determination of credit ratings of issuers and instruments. A list of sector and cross-sector credit rating methodologies can be found here.

A comprehensive technical description of the default model (PD Model) and the severity model (LGD Model), can be found in the following technical supplements: Modeling the Probability of Default and Modeling Loss Severity Given Default.

For data summarizing the historical robustness and predictive power of credit ratings, please click here.

For further information, please refer to *Rating Symbols and Definitions*, which includes a discussion of Moody's Idealized Probabilities of Default and Expected Losses, and is available here.

» *contacts continued from page 1*

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