CMM Model
Ongoing Model Performance Monitoring Report

By Model Development and Analytics Group

Q4 2024

Contents

1 Overview

This document presents the results of the latest ongoing model performance monitoring of the Commercial Mortgage Metrics ("CMM") model from Moody's for the purpose of calculating current expected credit losses ("CECL") for East West Bank's ("EWB's" or "the Bank's") US Commercial Real Estate ("CRE") loans, which include Income Producing Real Estate (both CRE and MFR), Construction and Land.

The purpose of the ongoing performance monitoring is to evaluate the model performance periodically, by reviewing the model prediction against actual losses and relevant statistical metrics. Through ongoing monitoring efforts coupled with practical use experience through quarterly allowance reporting, the Bank can evaluate whether the changes in risk drivers or macro-economic conditions require any model adjustment, re-development, or management overlay.

1.1 CMM Methodology

The CMM modeling framework comprises a network of interconnected models that fall into two modeling engines. The first engine models the impact of macroeconomic conditions on CRE market factors. The second engine models how CRE market conditions, together with loan and property-level characteristics, determine CRE loans' credit risks. This integrated modeling feature allows macroeconomic assumptions to logically flow through CRE market factors and location, asset, and loan-level details to enable the most accurate conditional loss estimates under different scenarios.

Among other risk metrics, CMM outputs the following:

- **Expected Default Frequency ("EDF").** The EDF credit measure is the probability that a CRE loan will experience a default event in the future. This statistic is monitored as PD in the performance monitoring process.
- **Loss Given Default ("LGD").** LGD is the statistically expected loss conditional on default. Specifically, LGD is the sum of (1) the loss from principal, which is the loss due to the difference between a collateral property's liquidation value and the unpaid principal balance of the commercial mortgage, and (2) the loss due to costs and expenses, including lost interest, transaction cost, legal and administrative expenses, price appreciation/depreciation after default, property maintenance, etc.
- **Expected Loss ("EL").** EL is the unconditional expected loss on a loan. Mathematically, for a given point in time, EL = EDF x LGD. This relationship also holds for cumulative holding period measures. The predicted error is predicted loss rate (i.e., EL) - actual loss rate. The EL is monitored by comparing the predicted EL with the actual loss rate.

Moody's "Modeling Commercial Real Estate Loan Credit Risk: CMM 3.0 Methodology Paper"[1] provides an in-depth discussion of the CMM EDF and LGD engines, underlying development data, and validation results. In addition,

[1] Bao, Eric, Jun Chen, Wenjing Wang, Megha Watugala, Jing Zhang. "Modeling Commercial Real Estate Loan Credit Risk: CMM 3.0 Methodology Paper." Moody's Analytics. December 2016.

the Bank completed a model calibration in September 2024 to ensure the EL measures from the Moody's model appropriately reflect the loss experience of the Bank's internal data.

1.2 Assessment Categories

The performance monitoring statistical metrics are classified into three categories – Good, Acceptable and Weak. The three assessment levels are marked as green, yellow, and red, respectively.

Assessment Outcome	Escalation Plan
Good	Assessment indicates satisfactory performance. No further action is required.
Acceptable	Assessment indicates acceptable performance. There could be opportunity for model owner to perform additional analysis. Depending on the nature of the test measure, this could indicate early signs of model weakness. Further investigation may be required
Weak	Assessment indicates poor performance. Root cause investigation is required when appropriate. Based on the outcome of the analysis, depending on the nature of the test measure, management will determine the most appropriate mitigation plan, including recalibration or re-development if warranted

1.3 Monitoring Data

The data sets for the current ongoing monitoring consist of quarterly inputs and outputs for the CMM model runs from March 2020 to December 2024, along with an updated loan performance data that has a cumulative net charge-off information for the CMM loans through December 2024. The loan performance data is obtained from REVOLV, the CECL production environment maintained by Data Management & Integration ("DMI"). We have also leveraged a consolidated CMM data set provided by DMI that was primarily used to perform the CMM model recalibration during Q3 2024, which runs from June 2007 to December 2019. Furthermore, we appended CMM model outputs from March 2020 to December 2024, obtained as part of the production runs, to the recalibration dataset. We utilized the recalibrated multipliers to obtain predicted lifetime loss rates for the entire data set.

The monitoring period ends in December 2024 for data. Statistics are calculated based on the whole monitoring period, if applicable.

Items	Monitoring Period	Time Window
Data (CSI)	Quarterly from Mar 2024 to Dec 2024	Each quarter
Statistics (PD)	Quarterly from Mar 2024 to Dec 2024	One year look back
Statistics (LGD)	Quarterly from Mar 2024 to Dec 2024	Each quarter
Statistics (EL)	Quarterly from Mar 2023 to Dec 2024	Each quarter

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2 Model Variables – Characteristic Stability Index

The population stability index ("PSI") is used to measure shifts in the underlying data and hence assess its stability. When this metric is applied to the model's independent variables, the outcome is often known as Characteristic Stability Index ("CSI"). PSI or CSI measures how much a variable has shifted in distribution over time when compared to the benchmark. Although a high PSI or CSI value itself may not indicate any potential weakness in the overall model performance, it is a useful measure to supplement the diagnosis when other statistical metrics signal a clear deterioration of model performance.

The CSI is calculated using percentage of balance following the formula below:

$$CSI(t) = \sum_{bin\ i} (P_i(t) - P_i(t-1)) * \ln\left(\frac{P_i(t)}{P_i(t-1)}\right)$$

Where $P_i(t)$ is percent of balance for bin i. Here, time t-1 refers to current time minus 1 year. Since CMM is an off-the-shelf Moody's model (albeit with EWB EL multipliers), it does not make sense to use the actual model development sample as the benchmark. Hence, we have chosen to use the portfolio data of the previous year to assess population shifts.

The following table shows the CSI criteria as outlined in the performance monitoring plan.

CSI Value	Description	Assessment Outcome
<= 0.10	Insignificant population shift	Good
> 0.10 and <= 0.25	Minor population shift	Acceptable
> 0.25	Significant population shift	Weak

The main loan-level risk drivers for CMM model are DSCR, LTV, Property Type, Metropolitan Area. The latter is derived by the model based on Zip Code and State. Note that DSCR and LTV are derived by the CMM model based on Net Operating Income (NOI) and the property's market value in relation to mortgage payments and balance. As a result, they tend to fluctuate with the market forecasts; thus, we do not apply the above assessment thresholds to the CSI outcome of DSCR and LTV.

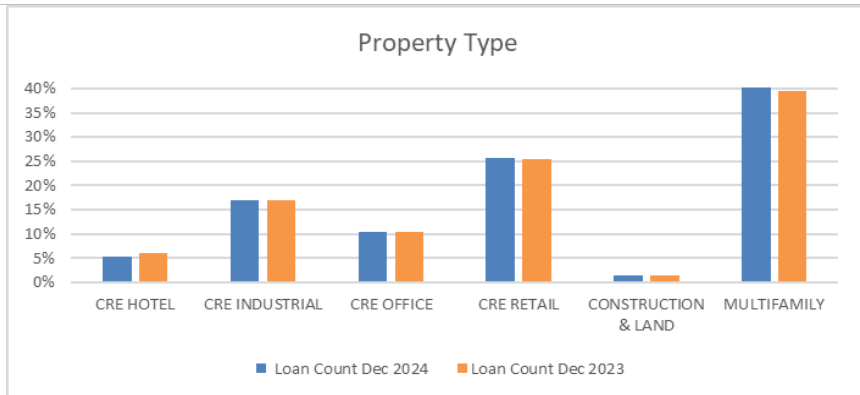
For each variable below, we calculate the CSI for the latest four monitoring quarters; in addition, we show the comparison of variable distribution by loan count between recent quarter Q4 2024 and prior year Q4 2023.

2.1 Property Type[2]

CSI values of Property Type indicate that the population distribution has been stable.

Table 1: Property Type — CSI and Distribution

Analysis Date	Property Type
Mar 2024	0.00
Jun 2024	0.00
Sep 2024	0.01
Dec 2024	**0.00**

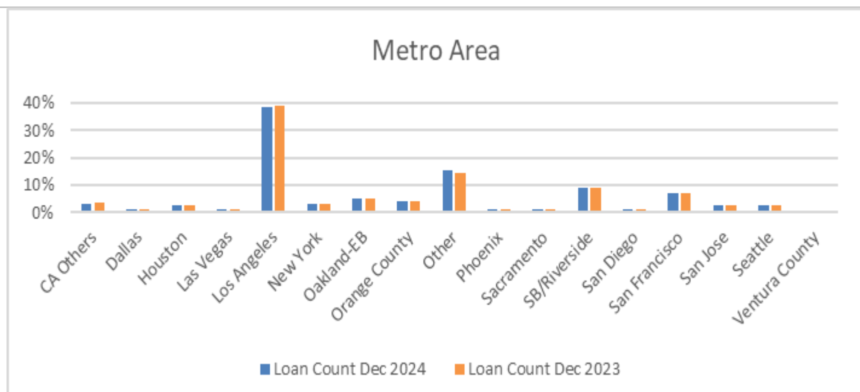


2.2 Property Metropolitan Area

We aggregated metropolitan areas into 17 groups based on balance, considering cities outside of California where the Bank has significant presence (see the chart below for the grouping). The CSI results show that the population distribution is stable.

Table 2: Metro Area – CSI and Distribution

Analysis Date	Metro Area
Mar 2024	0.01
Jun 2024	0.01
Sep 2024	0.01
Dec 2024	**0.01**



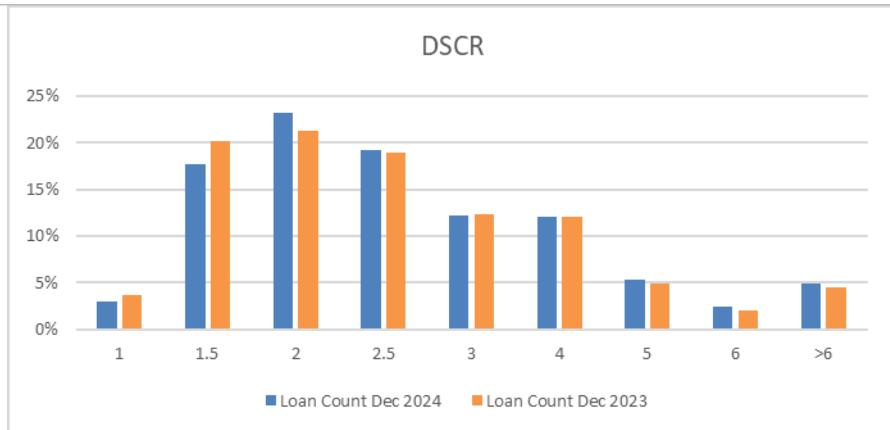
[2] The property types in this section are consistent with the segments for multipliers.

2.3 Debt Service Coverage Ratio (DSCR)

Loan-specific DSCR is derived within the CMM model based on NOI and periodic mortgage payments. CSI is calculated by comparing the DSCR distribution of December 2024 over analysis date one year before, December 2023.

Table 3: DSCR – CSI and Distribution

Analysis Date	DSCR
Mar 2024	0.01
Jun 2024	0.01
Sep 2024	0.01
Dec 2024	**0.04**

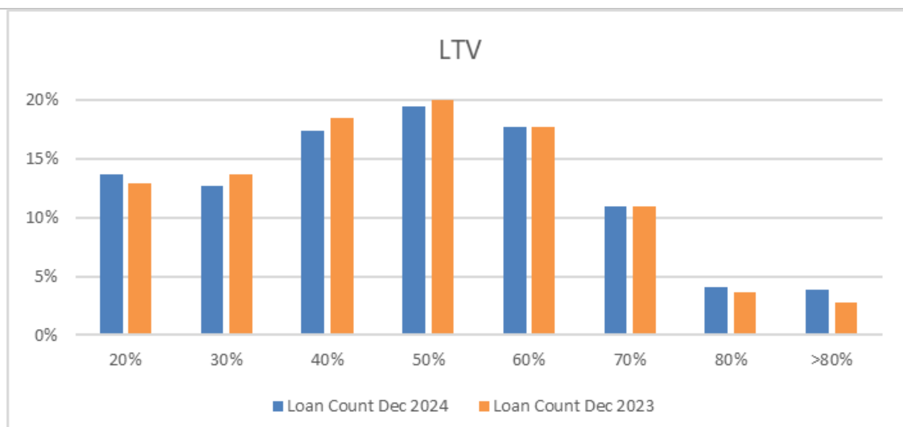


2.4 Loan To Value (LTV)

Similar to DSCR, LTV is derived within the CMM model based on property value and loan balance. Hence, it is not surprising that as the real estate market fluctuates, the LTV would rise and fall correspondingly. The CSI result of LTV shows no significant population shift compared to one year prior.

Table 4: LTV — CSI and Distribution

Analysis Date	LTV
Mar 2024	0.04
Jun 2024	0.01
Sep 2024	0.02
Dec 2024	**0.01**



3 Probability of Default Model

A key component of the CMM loss model is the EDF or Probability of Default ("PD") model. Although the model parameters are not accessible, the outputs of CMM allow us to examine the performance of the EDF model.

The pre-defined tests, Accuracy Ratio ("AR") and Kolmogorov-Smirnov ("KS") statistics, applicable to the PD model when # defaults >=5. The AR and KS statistics show that the model has good discriminatory power. A 12-month monitoring cohort is used to calculate the statistics.

AR **Criteria**	KS **Criteria**	**Assessment Category**
AR > = 0.4	KS >= 0.2	Good
0.4 > AR >= 0.2	0.2 > KS >= 0.1	Acceptable
AR < 0.2	KS < 0.1	Weak

Table 5: CMM PD Performance Statistics

Analysis Date	**# Defaults**	**AR**	**KS**
Mar 2024	9	0.90	0.79
Jun 2024	8	0.66	0.71
Sep 2024	9	0.55	0.51
Dec 2024	**8**	**0.64**	**0.58**

4 LGD Model

We also compare the model predicted LGD with the actual LGD for the defaults that occurred from the beginning of January 2024 to the end of December 2024. The results are shown below, group by each quarter:

Table 6: CMM LGD Comparison

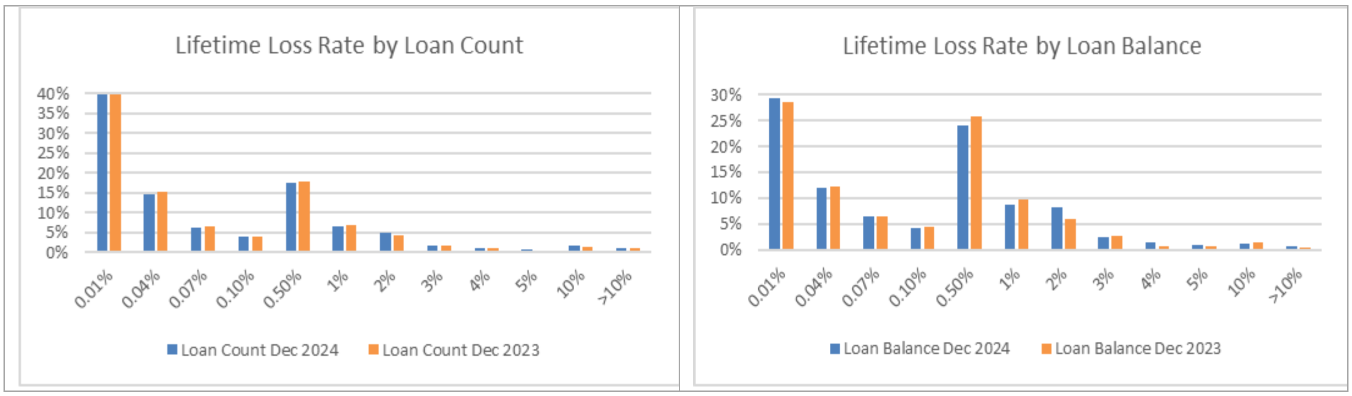
Analysis Date	**# Defaults**	**Actual LGD**	**Predicted LGD**
Mar 2024	3	26.91%	24.24%
Jun 2024	4	7.26%	19.77%
Sep 2024	1	0.00%	5.26%
Dec 2024	**0**	**0.00%**	**0.00%**

5 Predicted Lifetime Loss

5.1 Distribution of Lifetime Loss

The charts below show the distribution of predicted lifetime loss by loan balance and by loan count. Given the nature of lifetime loss rates (as a function of portfolio and macroeconomic variables), we do not apply the PSI evaluation criteria to this.

Table 7: Lifetime Loss Distributions by Loan Count and by Commitment Amount



5.2 Portfolio Level Prediction Errors

The CMM model does not provide confidence interval of the predicted values. Here, we track the prediction error ("PE") based on the RMSE of a "long-run" time series by merging the following: from Jun 2007 to Dec 2019, we leverage the actual and predicted values from the CMM model calibration performed in Q3 2024; subsequent quarterly data (Q1 2020 onwards) are obtained from the Revolv production environment. Although the underlying sample for the two sources may not be perfectly consistent, it sufficient for RMSE.

$$RMSE = \sqrt{\frac{\sum(Predicted - Actual)^2}{Number\ of\ Quarters}}$$

The prediction errors of lifetime loss rates are within the 95% confidence interval range of the predicted lifetime loss for the defined monitoring period. The actual loss rate typically should be lower than the predicted value during recent periods mainly due to the fact many of the loans in the portfolio are not yet matured and hence gone through its lifetime. The confidence interval is defined as (– RMSE * z, + RMSE * z), where z is the critical value. For 95% confidence interval, z=1.96. The assessment criteria are shown below:

Confidence Interval of PE	Assessment Category
-1.96*RMSE =< PE <= 1.96*RMSE	Good/Acceptable
-1.96*RMSE < PE > 1.96*RMSE	Weak

For the below analysis, RMSE is calculated with the "expanding window" approach, utilizing the entire time series of PE dating back to Jun 2007. For the pre-CECL production quarters, we leveraged the outcome of the model calibration analysis. We have included more past quarters (eight quarters in total) to provide a better comparison given the nature of the lifetime loss rates.

Table 8: Confidence Interval of Prediction Errors[3]

Analysis Date	Actual	Predicted	Prediction Error	Lower 95% Confidence Interval	Upper 95% Confidence Interval
Mar 2023	0.14%	0.44%	0.30%	-2.54%	2.54%
Jun 2023	0.14%	0.45%	0.31%	-2.52%	2.52%
Sep 2023	0.09%	0.53%	0.45%	-2.51%	2.51%
Dec 2023	0.05%	0.49%	0.45%	-2.49%	2.49%
Mar 2024	0.01%	0.49%	0.48%	-2.47%	2.47%
Jun 2024	0.00%	0.50%	0.50%	-2.46%	2.46%
Sep 2024	0.00%	0.45%	0.45%	-2.44%	2.44%
Dec 2024	**0.00%**	**0.56%**	**0.56%**	**-2.43%**	**2.43%**

5.3 Segment Level Prediction Errors

The segment level prediction errors are shown below. Here, we do not use the confidence interval assessment metric to evaluate the performance as the results may be over interpreted due to its granularity. The definition of segment is consistent with the multiplier calibration.

5.3.1 Construction and Land

Analysis Date	Actual	Predicted	Prediction Error	Lower 95% Confidence Interval	Upper 95% Confidence Interval
Mar 2023	1.68%	0.49%	-1.19%	-5.12%	5.12%
Jun 2023	1.57%	0.83%	-0.74%	-5.08%	5.08%
Sep 2023	0.25%	0.69%	0.44%	-5.04%	5.04%
Dec 2023	0.30%	1.27%	0.97%	-5.01%	5.01%
Mar 2024	0.00%	1.18%	1.18%	-4.98%	4.98%
Jun 2024	0.00%	1.70%	1.70%	-4.96%	4.96%
Sep 2024	0.00%	1.06%	1.06%	-4.93%	4.93%
Dec 2024	**0.00%**	**1.56%**	**1.56%**	**-4.91%**	**4.91%**

[3] The Actual Loss Rate reflects the realized losses associated with the defaults within the quarter, while the Predicted Loss Rate refers to the model prediction at the prior quarter.

5.3.2 CRE INDUSTRIAL

Analysis Date	Actual	Predicted	Prediction Error	Lower 95% Confidence Interval	Upper 95% Confidence Interval
Mar 2023	0.00%	0.02%	0.02%	-0.72%	0.72%
Jun 2023	0.00%	0.01%	0.01%	-0.71%	0.71%
Sep 2023	0.02%	0.02%	0.00%	-0.71%	0.71%
Dec 2023	0.02%	0.02%	0.00%	-0.70%	0.70%
Mar 2024	0.00%	0.02%	0.02%	-0.70%	0.70%
Jun 2024	0.00%	0.02%	0.02%	-0.69%	0.69%
Sep 2024	0.00%	0.03%	0.03%	-0.69%	0.69%
Dec 2024	**0.00%**	**0.04%**	**0.04%**	**-0.68%**	**0.68%**

5.3.3 CRE HOTEL

Analysis Date	Actual	Predicted	Prediction Error	Lower 95% Confidence Interval	Upper 95% Confidence Interval
Mar 2023	0.00%	0.22%	0.22%	-3.74%	3.74%
Jun 2023	0.00%	0.20%	0.20%	-3.71%	3.71%
Sep 2023	0.00%	0.22%	0.22%	-3.68%	3.68%
Dec 2023	0.00%	0.18%	0.18%	-3.65%	3.65%
Mar 2024	0.00%	0.16%	0.16%	-3.63%	3.63%
Jun 2024	0.00%	0.18%	0.18%	-3.60%	3.60%
Sep 2024	0.00%	0.17%	0.17%	-3.58%	3.58%
Dec 2024	**0.00%**	**0.28%**	**0.28%**	**-3.55%**	**3.55%**

5.3.4 CRE OFFICE

Analysis Date	Actual	Predicted	Prediction Error	Lower 95% Confidence Interval	Upper 95% Confidence Interval
Mar 2023	0.51%	0.59%	0.08%	-1.14%	1.14%
Jun 2023	0.51%	0.61%	0.10%	-1.13%	1.13%
Sep 2023	0.52%	0.92%	0.40%	-1.13%	1.13%
Dec 2023	0.23%	0.94%	0.70%	-1.13%	1.13%
Mar 2024	0.08%	1.00%	0.92%	-1.15%	1.15%
Jun 2024	0.00%	1.08%	1.08%	-1.17%	1.17%
Sep 2024	0.00%	0.91%	0.91%	-1.18%	1.18%
Dec 2024	**0.00%**	**1.45%**	**1.45%**	**-1.22%**	**1.22%**

The predicted loss rate for CRE Office in Q4 24 is outside of the upper confidence interval, primarily attributable to two large loans with property in Downtown San Francisco. The two submarkets particularly distressed with high vacancy rates and decreasing asking rent.

Loan ID	Balance (in millions)	Submarket in San Francisco	Loss Rate
MTV-00301002376-00001	$23.59	VanNess/Civic Center	47.89%
MTV-00769618718-00001	$36.65	Waterfront/North Beach	15.77%

Excluding these two loans from the CRE Office portfolio, we note that the predicted loss rate and prediction error for Q4 24 would have been 0.91% which is within the 95% Confidence Interval.

5.3.5 CRE RETAIL

Analysis Date	Actual	Predicted	Prediction Error	Lower 95% Confidence Interval	Upper 95% Confidence Interval
Mar 2023	0.00%	1.27%	1.27%	-2.79%	2.79%
Jun 2023	0.00%	1.23%	1.23%	-2.78%	2.78%
Sep 2023	0.00%	1.43%	1.43%	-2.78%	2.78%
Dec 2023	0.00%	1.11%	1.11%	-2.77%	2.77%
Mar 2024	0.00%	1.09%	1.09%	-2.77%	2.77%
Jun 2024	0.00%	0.92%	0.92%	-2.75%	2.75%
Sep 2024	0.00%	0.96%	0.96%	-2.74%	2.74%
Dec 2024	**0.00%**	**0.93%**	**0.93%**	**-2.73%**	**2.73%**

5.3.6 MULTIFAMILY

Analysis Date	Actual	Predicted	Prediction Error	Lower 95% Confidence Interval	Upper 95% Confidence Interval
Mar 2023	0.00%	0.08%	0.08%	-1.32%	1.32%
Jun 2023	0.00%	0.11%	0.11%	-1.31%	1.31%
Sep 2023	0.00%	0.14%	0.14%	-1.30%	1.30%
Dec 2023	0.00%	0.21%	0.21%	-1.29%	1.29%
Mar 2024	0.00%	0.22%	0.22%	-1.28%	1.28%
Jun 2024	0.00%	0.26%	0.26%	-1.27%	1.27%
Sep 2024	0.00%	0.18%	0.18%	-1.26%	1.26%
Dec 2024	**0.00%**	**0.21%**	**0.21%**	**-1.26%**	**1.26%**

6 Moody's Monitoring Outcome

Given that the current CMM model is an off-the-shelf product offered by Moody's, there is limited number of tests we could do on the Bank's data alone. To get further confidence on the model outcome, we reviewed the latest Moody's Model Validation and Monitoring Report[4]. Moody's concluded that CMM parameters are well-calibrated to the underlying dynamics of the commercial real estate market and both the EDF and the LGD models demonstrate satisfactory model performance.

Moody's CMM EDF model showed good performance by comparing results from the EDF model to loans' actual performance using key variables, such as location, property type, DSCR, and LTV.

Moody's also tested the LGD model to demonstrate its ability to predict LGD. The outcome of the analysis shows that the estimated LGD is within reasonable bounds to the actual LGD on the historical data post 2010.

Details can be found in previously submitted Moody's monitoring reports. There is no new CMM model monitoring report at the time of publishing this report.

[4] Sharif Amlani, Jun Chen, Junrong Liu, Megha Watugala. "CMM 3.0 – 2024 Model Validation and Monitoring Report Using 2023 Data." Moody's Analytics. 20 September 2024.