

**MODELING  
METHODOLOGY**FROM MOODY'S ANALYTICS  
QUANTITATIVE RESEARCH

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# Modeling Commercial Real Estate Loan Credit Risk: An Overview

*Version 2.0*

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**Abstract**

Commercial real estate (CRE) exposures represent a large share of credit portfolios for many banks, insurance companies, and asset managers. It is critical that these institutions properly measure and manage the credit risk of these portfolios. In this paper, we present the Moody's Analytics framework for measuring commercial real estate loan credit risk, which is the model at the core of our Commercial Mortgage Metrics (CMM)<sup>™</sup> product. We describe our modeling approaches for default probability, loss given default (LGD), Expected Loss (EL), and other related risk measures.

Our framework first models the CRE collateral stochastic process, as driven by both market-wide and idiosyncratic factors. We then apply a Monte Carlo technique to simulate the future paths of the collateral net operating income (NOI) and market value. A CRE loan credit event is doubly triggered by the collateral financial condition at the time of default: both the sustainable NOI falls below the total debt service, and the property market value falls below the total outstanding loan balance.

Moreover, in order to capture the actual observed borrower default behavior, we empirically calibrate the conditional probability of default (PD) function to large historical datasets. We also calculate the unconditional EDF<sup>™</sup> (Expected Default Frequency) credit measures as the integration of conditional PD values over the many future paths of NOI and market value. We model LGD through the same process; therefore, LGD and PD are structurally correlated and consistently estimated within the same coherent framework. Built upon EDF measures and LGD, we also calculate other measures such as EL, Yield Degradation (YD), Unexpected Loss (UL), and Stressed EDF measures and loss. By establishing a strong economic causality relationship between credit risks and real estate market- and property-specific covariates, the model also enables large-scale scenario analysis and stress testing.

Additionally, our model facilitates many different business applications, including loan origination, pricing and valuation, risk monitoring, surveillance, regulatory compliance, and portfolio management.



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# 1 Introduction

Commercial real estate (CRE) exposures represent a large share of credit portfolios for many financial institutions, including banks, insurance companies, and asset managers. According to the Federal Deposit Insurance Corporation (FDIC), CRE loans comprised about 22% (\$1.6 trillion) of all outstanding loans held by U.S. commercial banks and savings institutions as of September 2010.<sup>1</sup> For many insurance companies, CRE loans, with a total balance of approximately \$300 billion, represent an important asset class in their investment portfolios.<sup>2</sup> In addition, CRE instruments comprise a large portion of the underlying collateral backing structured products. Specifically, as of the third quarter of 2010, there was approximately \$706 billion outstanding in commercial mortgage backed securities (CMBS) owned by asset managers, banks, and insurance companies.<sup>3</sup> For these institutions, the risk that borrowers fail to pay either the interest and/or principal on these CRE loans poses a significant challenge. In fact, significant credit loss from commercial mortgages can often wipe out the capital cushion and lead to the failure of a financial institution. During the past 30 years, we have witnessed the failures of numerous financial institutions, both in the late 1980s to early 1990s and also in the recent financial crisis, caused to large degree by CRE-specific loan losses.

Given these challenges, financial institutions continue to seek better risk management of their CRE exposures. Toward this goal, the first step is to measure the credit risk of these CRE portfolios, including the standalone credit risk assessment of individual loans, as well as their correlation and concentration effects at the portfolio level. In this paper, we present the Moody's Analytics framework for measuring the credit risks of individual CRE loans. Specifically, we describe our modeling approaches for default probability, loss given default, Expected Loss (EL), and other related risk measures. For the Moody's Analytics approach for measuring CRE asset correlation within a portfolio context, see Patel and Zhang (2009).

In our framework, we begin by modeling the asset process of the underlying CRE collateral. We consider the stochastic evolution of a commercial property's financial performance, including income and market value, as driven by both market-wide and idiosyncratic factors. We first estimate the local market-specific parameters that govern those processes utilizing extensive historical datasets, then we apply a Monte Carlo technique to simulate the future paths of the collateral's net operating income (NOI) and market value. The Monte Carlo technique enables the model to capture the path-dependency of the survival probability and the remaining credit risks as the future unfolds.

An important model feature is that a CRE loan credit event is doubly triggered by the collateral financial condition at the time of default: both the sustainable NOI falls below the total debt service, and the property market value falls below the total outstanding loan balance. Moreover, since the CRE market operates in an opaque environment that is neither complete nor perfectly efficient, the conditional probability of the default (PD) function is empirically calibrated to large historical datasets in order to capture the actual observed borrower default behavior. We calculate the unconditional EDF (Expected Default Frequency) credit measure as the integration of conditional PD values over the many future paths of NOI and market value.

Finally, we model loss given default (LGD) via the same process; hence, LGD and PD are structurally correlated and consistently estimated in the same coherent framework. Built upon EDF credit measures and LGD, the model also calculates other measures such as EL, Yield Degradation (YD), Unexpected Loss (UL), and Stressed EDF measures and loss. By establishing a strong economic causality relationship between credit risks, the real estate market, and property-specific covariates, the model also enables large-scale scenario analysis and stress testing. Another significant benefit is our model's ability to accurately differentiate the credit risks of senior/junior structure of the multiple loans on the same collateral, as well as that of mezzanine loans.

In addition to the analytical modeling framework, we have sourced very extensive U.S. commercial real estate market data and forecasts at the metropolitan and submarket levels, where available. These local market data and forecasts are embedded within our Commercial Mortgage Metrics (CMM) system, making it a transparent, one-stop solution where users can consistently measure credit risks across different property types and geographic locations. In the meantime, the

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<sup>1</sup> FDIC Standard Report #5 (All Commercial Banks–National) as of 9/30/2010.

<sup>2</sup> Flow of Funds Accounts of the United States, third quarter 2010.

<sup>3</sup> The Compendium of Statistics, update December 30, 2010, published by the CRE Finance Council.

CMM system enables total control over the inputs on the collateral's most recent financial statistics, including NOI and market value (either transaction- or appraisal-based) together with loan characteristics such as coupon rates.

The credit measures produced by our model have many business applications for CRE practitioners. These include risk assessment and asset selection, risk-based pricing and valuation, risk monitoring and surveillance, regulatory compliance and internal control, loss forecast and provisioning, scenario analysis and stress testing, and portfolio management. For example, loan officers and underwriters can objectively and systematically assess the credit risks of a CRE loan located in any given U.S. market; at the back end, credit risk managers and portfolio managers can quickly monitor the most recent credit profiles of individual loans, as well as entire portfolios. By establishing a strong economic causality relationship between credit risks and real estate market and property-specific covariates, the model also enables large-scale scenario analysis and stress testing. For example, CMM allows users to compare results from a baseline scenario and a stressed scenario. Users can also input their own commercial real estate market-specific views and test credit risks from those views.

The remainder of the paper is organized as follows.

- Section 2 describes model outputs and their practical applications.
- Section 3 describes the modeling framework and inner workings of the model.
- Section 4 discusses the empirical data.
- Section 5 documents the model validation findings.
- Section 6 summarizes the paper and provides concluding remarks.

## 2 Model Outputs and Applications

In this section, we focus on the end results of our CMM model, and discuss how various practitioners can use these results to make more informed business decisions.

### 2.1 Model Outputs

The Moody's Analytics CMM model estimates the credit risk of commercial real estate loans, combining user-provided portfolios with market-wide data and forward-looking scenarios.

The model provides estimates of the following risk measures, both for a single commercial real estate loan as well as for a portfolio of loans.

- **EDF (Expected Default Frequency)** credit measure—measures the probability that a commercial real estate loan experiences a default event in the future. We estimate EDF credit measures throughout the loan term, and the model estimates an annual EDF measure for a particular point in time within the loan term. We then calculate cumulative EDF measures to measure the cumulative holding period risks.
- **Loss given default (LGD)**—refers to expected loss amount, typically as a percentage of outstanding unpaid loan balance, at the time of the default event, if the default event occurs.
- **Expected Loss (EL)**—measures the expected losses of a commercial real estate loan due to default events. Mathematically, for a given point in time,  $EL = EDF \times LGD$ . This relationship also holds for cumulative holding period measures.
- **Yield Degradation (YD)**—measures the annualized reduction of expected yields from a commercial real estate loan due to losses related to default events throughout the loan term. YD is similar to the measure of annualized EL, with the main difference being that YD takes into account the timing of expected losses and discounts losses according to the timing, whereas, annualized EL does not involve discounting and time-value of loss.
- **Unexpected Loss (UL)**—defined as a one standard deviation of loss from the loss distribution. We estimate the one standard deviation of loss based on a full range of loss distribution derived from Monte Carlo simulations of all possible combinations of systematic market risk factors and non-systematic idiosyncratic loan and property-specific risk factors.

- Stressed EDF measure and loss—measures the point estimate of EDF measures or loss from a full range of EDF credit measure or loss distribution derived from Monte Carlo simulations. Typically, we measure the Stressed EDF at a user-specified stressed point, such as a confidence level greater than 50%, for the tail risk at the right-hand side of the distribution.

## 2.2 Business Applications

Underwriters, credit officers, risk managers, and portfolio managers can use Moody's Analytics CMM for a variety of different business applications. For institutions that employ internal rating systems as the foundation of many business decisions, they can either map the EDF credit measures and LGD outputs to their internal rating scales, or combine them with other qualitative inputs to derive an internal rating. Alternatively, they can use CMM to benchmark and calibrate their own internal risk rating systems.

CMM applications include risk assessment and asset selection, risk-based pricing and valuation, risk monitoring and surveillance, regulatory compliance and internal control, loss forecast and provisioning, scenario analysis and stress testing, and portfolio management.

### Using CMM in Internal Ratings Systems

Internal rating systems serve as the foundation of many business decisions within financial institutions such as credit approval, limit setting, regulatory compliance, risk-based pricing, and active portfolio management. An effective internal rating system has the following attributes.

- Separates default and recovery risk.
- Provides powerful differentiation of relative ranking of risk.
- Well-calibrated to provide appropriate distinctions of risk.
- Contains well-documented definitions, assumptions, and methodologies.
- Combines qualitative assessment and quantitative assessment where appropriate.

We developed CMM with the above attributes in mind. CMM measures CRE loan default risk via EDF credit measures and recovery risk via its LGD. As shown later in this paper, the model proves to be powerful, forward-looking, and accurately calibrated to real loss experience. For documentation, this introductory paper, together with the detailed and comprehensive modeling documents, provides model transparency for users. Therefore, CMM is ideal as a quantitatively-based internal ratings system for CRE exposures. If institutions use internal rating scales not generated in absolute scales, such as PD and LGD, they can map the EDF credit measures and LGD outputs to their own internal rating scales.

Many institutions find that market-based information, when available, is particularly relevant and powerful in internal risk rating assessment. CMM credit measures utilize a significant amount of CRE market information, and we construct them to reflect all the relevant property type and location-specific market information. Thus, if the user finds it appropriate to combine qualitative assessment with quantitative components, CMM credit measures are particularly useful as the market-based quantitative assessment component of an internal rating system. In fact, we make it feasible and efficient to implement such an approach in the Moody's Analytics RiskAnalyst™ system. An internal rating system must provide sufficient differentiation of default risk. To calibrate such a system, regulators typically expect a sizeable amount of realized default events and loss severity data spanning at least a full economic cycle. Many institutions do not possess enough internal data and can benefit from using CMM credit measures to benchmark and calibrate internal risk systems.

### Risk Assessment and Asset Selection

CMM can be very effective during an institution's credit underwriting process. Commercial mortgage underwriters and credit officers can benefit significantly by using CMM to directly measure and compare credit risks at loan origination for given loan and property characteristics. For example, CMM allows users to run multiple "what-if" analyses to compare how credit risks, including PD, LGD, and EL, would change if either one or both the Debt-service Coverage

Ratio (DSCR) and loan-to-value (LTV) change. Underwriters can use this information to risk-base price loans according to a specific combination of DSCR and LTV.

Another invaluable feature of CMM is its embedded local real estate market data and forecasts, which make it possible to compare loan risks across different property types and geographic locations. For example, a national financial institution often conducts CRE lending in many locales throughout the country, and individual underwriter expertise and assessment may vary significantly between local offices. CMM enables centralized credit risk management to objectively and consistently measure credit risk without overly relying upon individual judgments from dozens of or even hundreds of different credit underwriters.

### **Risk-based Pricing and Valuation**

A financial asset such as a commercial mortgage must be appropriately compensated for its given risks. Because commercial mortgages fit well in held-for-investment portfolios, the long-term credit risks become, *de facto*, the most important source of risk. As such, CMM can help determine the trade-offs between loan pricing and future risks. This type of risk-based pricing and valuation can be performed both at the primary market and the secondary market levels.

### **Risk Monitoring and Early Warning**

The credit quality of commercial mortgages can change quickly as the market environment or property-specific conditions change. Because the credit risk measure outputs from CMM are objective and forward-looking, risk managers can target their risk assessment and mitigation resources toward cases where they can be the most effective. Annual reviews and other traditional credit processes cannot maintain the same degree of speed, consistency, and objectivity. Within CMM, accurate and timely information from the commercial real estate market can be applied consistently across the entire portfolio, which is often difficult and expensive to duplicate using traditional credit analysis processes.

### **Regulatory Compliance and Internal Governance**

The probability of default associated with an internal rating plays a central role in the calculation of capital requirements within the Basel II framework. Banks may use external PD models, such as EDF measures from CMM, as part of their internal ratings, either for regulatory capital calculations or for fulfilling internal governance and external regulatory requirements.

### **Loss Forecast and Provisioning**

Loan loss provisions are expenses charged to a bank's earnings when adding to the allowance for possible bad debt. In estimating the provisioning amount, one can use a credit risk model to estimate the potential credit losses on loans. The model should respond to changes in the risk environment across the economy as a whole. In other words, a provisioning calculation should be as forward-looking as possible. In fact, both the International Accounting Standard Board (IASB) and the Basel Committee on Bank Supervision are moving toward the more forward-looking "expected loss" approach and away from the "incurred loss" approach (e.g., Basel Committee on Banking Supervision, 2009). All CMM credit measures are forward-looking assessments that respond to changes in the CRE market cycle and produce accurate estimates of credit losses over a long period. Consequently, these credit measures are appropriate for expected loss-based provisioning calculations.

### **Scenario Analysis and Stress Testing**

The future remains inherently uncertain. No single person or entity, nor the market as a whole, possesses a crystal ball that predicts exactly what will occur. We built the CMM system so that it contains several embedded commercial real estate market forecast scenarios, and also allows users to input their own views regarding specific property types and/or geographic locations. Such functionality is particularly valuable for risk managers when comparing possible outcomes from different economic outlooks. Forecast scenarios are also becoming more and more a daily business necessity, given increased regulator and internal risk controller requirements for periodic stress tests. The CMM on-demand scenario analytic capabilities can significantly improve an institution's readiness to meet such continuous demands.

## Portfolio Management

Portfolio management entails making numerous decisions, such as taking on additional exposures, selling or hedging existing exposures, and calculating the prices at which to do so. The Moody's Analytics CMM system provides a framework that enables you to make informed decisions regarding which loans to create, under what terms, and at what price(s). In addition, risk managers can use CMM portfolio functionality to construct strategies that exploit the relative price differences between property types and local CRE markets. Additionally, the EDF measures and LGD outputs from CMM can serve as inputs to calculations performed by portfolio management systems such as Moody's Analytics RiskFrontier™.

# 3 Modeling Framework

In this section, we first describe how credit events occur for commercial real estate loans in the real world. We use an example to illustrate the importance of the collateral financials in affecting a loan's credit risk. Next, we present the conceptual framework as well as details of the model's inner workings, including specifics on the asset process, the PD model, and the LGD model. We then describe how the components work together within the CMM system. Finally, we explain how CMM implements scenario analysis and stress testing.

## 3.1 Understanding Commercial Mortgage Credit Events

Since our objective is to accurately measure the probabilities of a credit event occurring and the resulting losses associated with the credit events, first and foremost, it is important to examine why and how credit events and losses happen in the real world. We want to make sure our model succinctly and consistently emulates real world phenomena and captures its essence.

Why would any commercial real estate loan borrower default on their debt obligations? In principle, there are two primary reasons under the so-called double trigger framework. The first is that cash flow from the property is inadequate to cover the scheduled mortgage payment; the second is that the underlying commercial properties, which serve as the secured collateral for most commercial real estate loans, are worth less than the mortgages. In other words, a commercial mortgage borrower's ownership value, inclusive of property resale value, plus current and future incomes, less the market value of the mortgage (including current outstanding payments), becomes less than zero in the event of default. We point out that the borrower's equity value is its economic value and takes into account embedded options, so it may differ from the book equity measure. Also, because commercial real estate is an asset class primarily focused on producing an inflation-adjusted rental income stream while preserving capital value, it is more productive to separate and focus on the income side of the ownership value. We illustrate the double trigger framework with the following example.

### Double trigger framework example

When a commercial mortgage is originated, the mortgage lender typically requires cushions in both leverage and debt service coverage. For example, a LTV ratio of 70% and a DSCR of 1.30 may be the threshold underwriting criteria for a particular lender. Under this threshold, the maximum loan amount a borrower can obtain is \$7,000,000, if the market value of the property is worth \$10,000,000; and the maximum annual debt service a lender would allow is \$538,462, if the property is currently generating \$700,000 in annual net operating income (NOI). In fact, since both ratios need to satisfy the threshold underwriting ratios, the actual mortgage may either carry a loan amount of less than \$7,000,000 or the annual debt service is less than the \$538,462. The point here is that most commercial mortgages, if underwritten appropriately and absent of fraud, should, in theory, carry no or very little credit risk at origination. What drives the credit risk is the inherent future uncertainty, which can potentially be quantified.

For simplicity, assume that a commercial mortgage originates with \$7,000,000 loan amount, with annual debt service of \$538,462, based on a \$10,000,000 property generating \$700,000 NOI a year. The realization of future NOI of the property is unknown and can follow an infinite number of possible paths. In the particular NOI path illustrated in Figure 1, there are periods around points A and B where the collateral's NOI is not sufficient to cover mortgage payments.

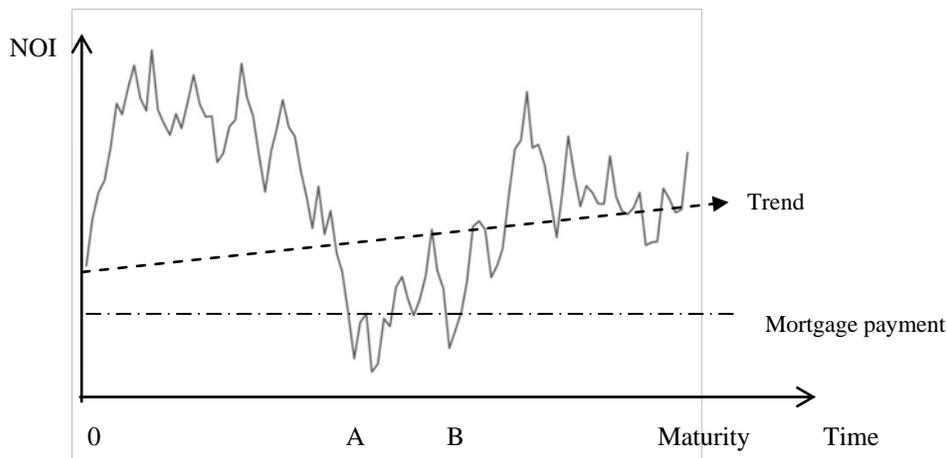


Figure 1 Evolution of a collateral property's NOI

Whenever a property is not generating enough NOI to cover the periodic mortgage payment, a borrower must weigh the different options, as follows.

- Cover the payment shortfall from their own pocket, if the shortfall is deemed temporary and will be cured.
- Sell the underlying property and pay back the entire remaining mortgage balance, including outstanding interest payments, if the market value of the underlying property is enough to cover all debt obligation plus a non-trivial transaction cost.
- As a last resort, miss the mortgage payments and wait for the lender's decision to either foreclose or restructure debt.

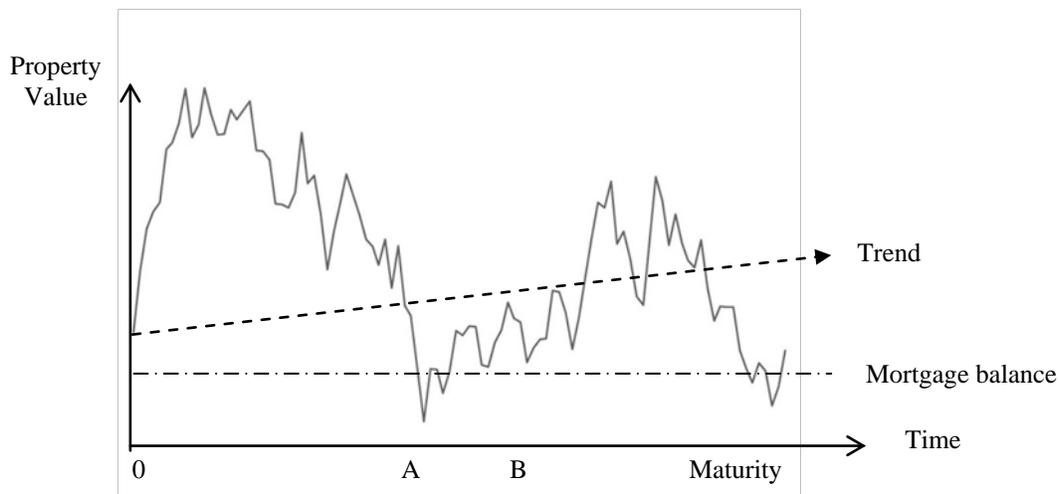


Figure 2 Evolution of a collateral property's value

Obviously, what is also very important in this situation is the market value of the property, pledged as secured collateral, which the lender can take possession of in the event of default. While the property value is usually correlated with NOI, its evolution is also affected by the general conditions in both capital and space markets, in addition to the property-specific NOI. In our example, with the particular NOI realization as in Figure 1, the property value does not necessarily follow the NOI movement in lockstep.

As illustrated in Figure 2, the property value drops below the mortgage balance around point A, but not point B. Toward the end, the property value declines again around loan maturity even though the property’s NOI remains well above the scheduled mortgage payment amount, shown in Figure 1.

It is straightforward to make the following observations with this particular example, as shown in Table 1.

Table 1 Decision analysis on default probabilities

Decision Point	DSCR	LTV	Decision Analysis	Credit Risk Measurement
A	< 1.0	> 100%	High probability of default	EDF <sub>A</sub>
B	< 1.0	< 100%	Not a clear-cut default choice	EDF <sub>B</sub>
Maturity	> 1.0	≈ 100%	High refinancing risk	EDF <sub>Maturity</sub>

While the above discussions illustrate the financial aspects of CRE borrower default drivers, we should note that decades of actual experience with commercial mortgage defaults also clearly teach us that a borrower’s decision to default is not purely a financial matter. For a CRE asset that is illiquid and difficult to value and to sell easily, the borrower’s decision to default is influenced by both financial facts and subjective assessment of the situation, leading to the so-called “sub-optimal” (non-ruthless) default behaviors observed at the aggregate level.<sup>4</sup> We emphasize here that a vast majority of borrowers do make very rational and near-optimal decisions regarding defaults; it is the inability to observe and record many loan, property, and borrower-specific decision factors that lead to empirically-observed, “sub-optimal” default rates in aggregate. Furthermore, even perfectly explainable and rational behavior on the individual level can still appear to be “sub-optimal” using aggregate data alone.

To create a credit risk model that is relevant for business users, we must anchor the analysis on empirical data. While theoretical thinking is very useful as a starting point in disentangling the causes and consequences from a rational economic-reasoning perspective, a model will not be accurate and useful for business applications if it is simply an intellectual exercise without the benefit of actually-observed historical data. Thus, our approach to modeling CRE credit events is to combine rational economic reasoning perspectives with insights gleaned from careful analysis of empirical data.

## 3.2 Model Setup and Details

Because commercial mortgage credit events fundamentally depend on the realized financial conditions of the underlying collateral and the market environment it operates within, our modeling process starts by understanding and quantifying the dynamic processes and uncertainties surrounding CRE assets. In addition, at the time of financial distress, because commercial mortgage borrowers make default decisions based beyond purely financial considerations, we employ empirical data and statistical analysis to measure the “sub-optimal” or “behavioral” aspect of mortgage defaults. In other words, our modeling framework can be thought of as consisting of two major parts: the underlying commercial properties’ stochastic dynamics following a structural approach; and empirically calibrated default probability measurements, conditional upon realized property financials.

<sup>4</sup> Note here that “sub-optimal” is viewed from the borrower’s perspective. In fact, since the lender takes the opposite position, the “sub-optimal” borrower’s behavior actually adds value to the lenders’ CRE portfolio. Because, in aggregate, CRE borrowers do not exercise their default options ruthlessly, most lenders’ CRE operation has been able to live through the cyclical troughs of the CRE market downturns without being completely destroyed.

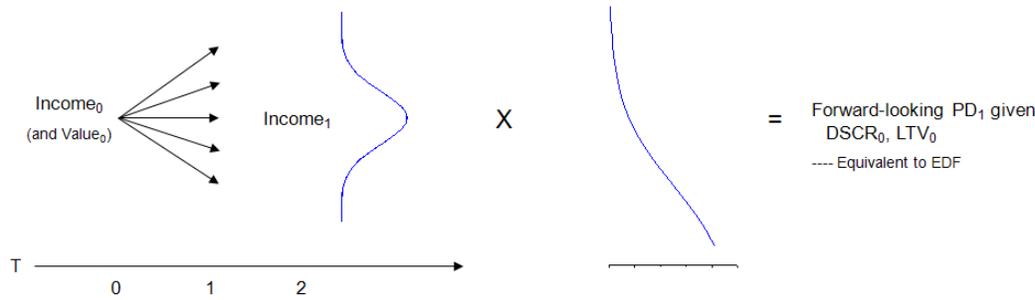


Figure 3 The CMM modeling framework consists of two major parts

Mathematically, a commercial real estate loan's EDF credit measure at a particular point in time  $t$  is:

$$EDF_t = \int Prob(X_t) \cdot Prob(Default|X_t) \quad (1)$$

where  $X_t$  denotes all the relevant financial variables at the loan, property, and market levels measured at time  $t$ ,

$Prob(X_t)$  measures the probability of a particular realization of  $X_t$ ,

and  $Prob(Default|X_t)$  is a conditional default probability function given the realized  $X_t$ .  $EDF_t$ , (i.e. the unconditional  $EDF$ ), is simply an integration of the probabilities of all possible realizations of  $X_t$  multiplied by corresponding conditional default rates for those realizations.

We find that this composite modeling approach leads to the most effective credit risk model by combining the best of both worlds. On the one hand, the dynamics of variable,  $X_t$ , follows a structural stochastic process that is fully parameterized based on extensive historical observations of the commercial property financials. On the other hand, the calibration of the conditional default rate function  $Prob(Default|X_t)$ , derived from rigorous statistical analysis, captures the “sub-optimal” exercise of the default options, and therefore, produces accurate and realistic EDF measures. This composite approach is similar in spirit to the Moody's Analytics EDF credit measure model approach for publicly traded firms, as that model is also a structural approach with a robust implementation grounded in empirical data.

Another benefit of our modeling approach is that it naturally leads to LGD measures that are economically and structurally correlated to PD, because  $LGD_t$  can be estimated as another conditional function that draws  $X_t$  as the dependent variables. This method offers significant improvement over an ad hoc approach to approximate the relationship between PD and LGD.

In essence, our CMM model consists of three key elements.

- Parameterizations of Asset Dynamics and Volatility (the Asset dynamics model). In this step, the CRE collateral's NOI and value processes in the future are parameterized, based on its property type and geographic location, in conjunction with the known financial and leasing information at the starting point.
- Calculation of EDF Measure (the EDF model). At a future time  $t$ , given realized NOI and values generated by Monte Carlo simulations, the model first calculates the default drivers, including DSCR and LTV, and then estimates conditional PD through the conditional default rate function  $Prob(Default|X_t)$ . Provided by the known distribution characteristics of NOI and value from the first step, the model then estimates unconditional EDF measures as well as Stressed EDF measures as point estimates from the full range of conditional PD distributions.
- Calculation of LGD (the LGD model). Given a simulated market value of the collateral at a future time  $t$ , the model estimates conditional LGD through an empirically-determined loss function. An unconditional LGD is the weighted sum of conditional LGD values, with weights being the corresponding conditional PD values.

We can also easily calculate other risk measures such as EL, UL, and yield degradation since the model performs a full Monte Carlo simulation from which EDF measures and LGD have been calculated. The remainder of this section offers a brief introduction to these key model elements.

### 3.2.1 Asset Dynamics and Volatility

Asset dynamics refers to the inner workings and quantifiable causal relationships of the commercial properties' financial performance, and asset volatility refers to the uncertainty around the financial performance. While conceptually one can measure all sorts of financial-related variables including rents, occupancy rates, revenue, expense, NOI, capital expenditure, and market value etc., the direct drivers behind commercial mortgage defaults are mainly DSCR and LTV, which are, in turn, driven by NOI and the property's market value.

Modern financial theory views any asset, including commercial real estate, as having two independent sources of risk drivers:

- One related to the overall market movement, also known as market or systematic risk
- Another related to the specifics of individual assets, also known as non-systematic or idiosyncratic risk

Intuitively, this separation is no different than the commonly practiced attribution analysis, where both performance (returns) and risks (volatility) can be traced back to either market-wide trends or asset-specific conditions. It has been established that the process of a commercial property's income or value can be approximated as follows:

$$P_{i,t} = P_{m,t} + \varepsilon_{i,t} \quad (2)$$

$\nearrow$   
 Systematic  
 component

$\nwarrow$   
 Non-systematic  
 component

where  $P_{i,t}$  represents the realization of NOI or value in log form for the  $i$ th property at time  $t$ , and  $P_{m,t}$  represents the market-wide index at the same time  $t$ , and  $\varepsilon_{i,t}$  is the idiosyncratic component of the  $P_{i,t}$  movement that remains after stripping out the market-driven component.

The specification also means that, in terms of risk composition,

$$\underbrace{\text{Variance } [P_{i,t}]}_{\text{Total risk}} = \underbrace{\text{Variance } [P_{m,t}]}_{\text{Systematic risk}} + \underbrace{\text{Variance}[\varepsilon_{i,t}]}_{\text{Non-systematic risk}} \quad (3)$$

The importance of a risk model when considering both systematic and idiosyncratic risks is illustrated in Figure 4, which shows a typical CRE asset that displays substantially higher total risk than market risk alone.

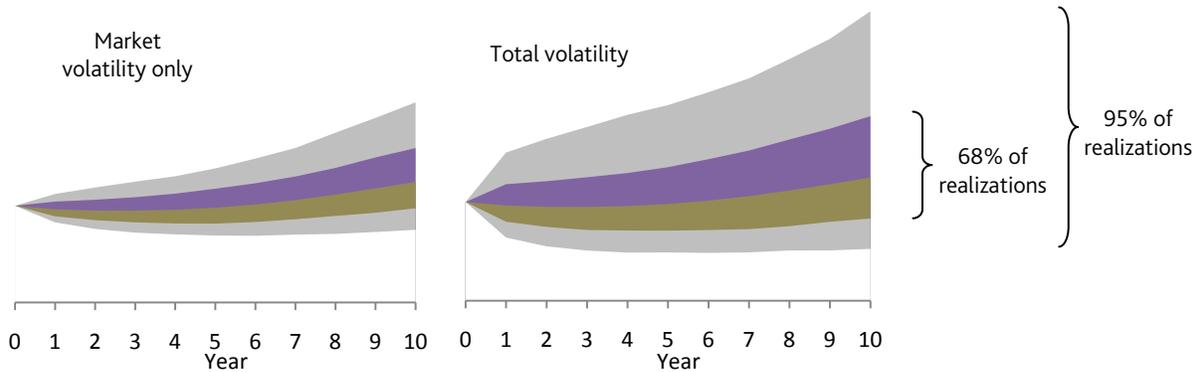


Figure 4 Distributions of NOI amounts or values

Because real estate is a very location- and property type-specific business, the market here is defined by property types and metropolitan areas. In other words, the San Francisco office market is considered a distinct market from the San Francisco apartment market or the New York office market, and so on. Drawing from a large historical time-series database, which includes both market-wide performance statistics and property-specific operating financials covering a substantial portion of the U.S., we can estimate and parameterize the asset dynamics and volatilities as specified in Equations (2) and (3) for most of the active CRE markets in the U.S.

To help understand how CMM implements the Monte Carlo simulations of the collateral NOI, we provide an example of the actually observed property-level NOI values of office properties in the San Francisco office market.

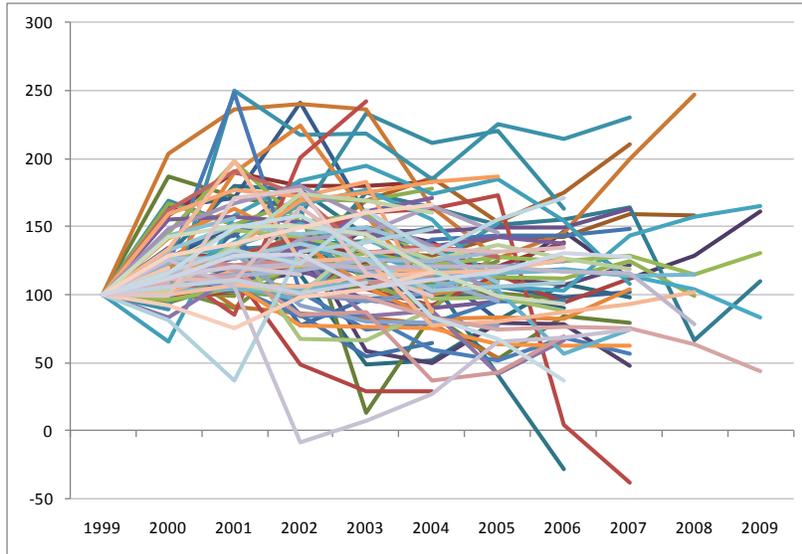


Figure 5 Property-level observations of normalized NOI for San Francisco office properties.

Since DSCR is determined to be the most important empirical variable, in CMM Monte Carlo simulations, we focus on the NOI simulations based on the observed historical patterns by property type and metropolitan areas, such as the one shown in Figure 5. In particular, we simultaneously simulate the random realization of independent factors: the market-wide and the property idiosyncratic factors. For example, as shown in Figure 6, the market factor could rise, stay flat, or lower in the future.

Meanwhile, a particular realization of the collateral's NOI can also deviate from the market factor by idiosyncratic variations. Given a particular realization of the market path, the final realized NOI could be better than, the same as, or worse than the market-wide growth rates. We have observed in the actual model implementation that the end results of CMM's NOI simulations for the San Francisco office market are indeed quite similar to that shown in Figure 5, which confirms the validity and robustness of our collateral models.

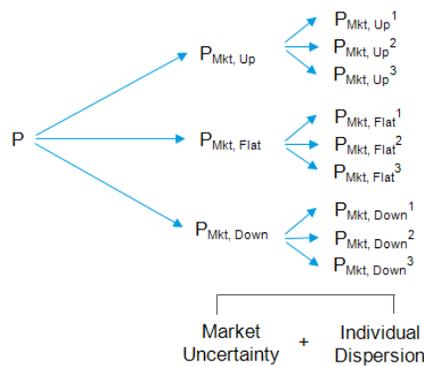


Figure 6 The asset risk of a commercial property comes from both market and idiosyncratic sources

### 3.2.2 Modeling Conditional Default Probability

Once we fully specify the asset processes, the next problem is to solve the probability of borrowers choosing to default, based on a particular realization of NOI and market value of the underlying collateral. Fundamentally, this is a question about the conditional default probability. Note, that in an abstract structural default modeling approach, such as the Merton model, a loan would automatically default once the market value of the asset falls below that of the mortgage, since the amount of the debt serves as the absorbing boundary. While still incorporating this powerful notion, our modeling framework expands to include the following very important practical considerations, making the model truly relevant in the real business world.

- The market value of a specific asset is actually unknown and is a somewhat subjective measure in the case of commercial real estate. As such, in an empirical model, we must resort to other directly-observable measures to complement imprecise measures of the asset value. It is also important to recognize that a periodic income stream should be explicitly factored into the valuation equation of a CRE asset.
- Net operating income (NOI), which is directly observable and ubiquitously measured and recorded, is of predominant financial and decision-making importance to commercial mortgage borrowers. Notice that a particular CRE asset is fundamentally an income-producing asset, and, unlike a corporation, it has no potential to grow its business base, since its physical size and location are fixed once built. As we find throughout our empirical work, the debt-service-coverage ratio (DSCR), which measures the level of NOI relative to the periodic mortgage payments, explains a large portion of the historical default incidents.
- Defaulting (or not) is a borrower's choice, rather than a strict rule that must be followed. While financial factors such as DSCR and LTV are of critical importance, choices are behavioral in nature and subjective to both quantifiable and non-quantifiable factors. Note here, we consider that the conditional default rate is not only a default probability conditional upon known financial and operating ratios, but it is also a probability of a borrower choosing to default. To date, it appears to us that the best way to model this kind of behavioral issue is through extensive statistical analysis using large panel datasets, which is exactly what we incorporate.

Effectively, our conditional default probability model is a multi-factor empirical function that links empirical default rates to key explanatory variables at both the property/loan and the market levels. Our empirical research identifies the following key statistically-significant variables in explaining historical defaults.

- Asset level financial ratios: DSCR, LTV, and collateral size
- Market cycle factors: vacancy rate, market-wide price changes, and market condition at origination
- Other: core vs. non-core collateral and loan seasoning

The functional model form looks like:

$$Prob(Defaul t|X_t) = f[T_1(DSCR_t), T_2(LTV_t), \dots] \quad (4)$$

where  $X_t$  denotes all the explanatory variables listed above,

$T_1$  and  $T_2$  are semi-parametric transformations of DSCR and LTV,

and  $f$  is a logistic function to capture the non-linear relationship between PD and explanatory variables.

Table 2 Explanatory variables in the conditional default probability model

No	Category	Measurement	Relationship
1	Debt Coverage	Monotonously transformed DSCR (debt-service-coverage ratio).	Lower DSCR leads to higher PD.
2	Financial Leverage	LTV (loan-to-value ratio)	Higher LTV leads to higher PD.
3	Systematic Factor (Space Market)	Standardized market-wide vacancy rate (i.e. z-score for space market).	Weak space market (higher vacancy rate) leads to higher PD.
4	Systematic Factor (Capital Market)	Standardized market-wide price change (i.e. z-score for year-to-year price change).	Weak capital market (slower and negative price appreciation) leads to higher PD.
5	Origination Quality	Transformed market-wide vacancy rate at loan origination.	Loans originated in stronger CRE market environment tend to have higher PD due to loosening of the underwriting criteria.
6	Collateral Size	Percentile of property size for corresponding types.	Larger collateral leads to higher PD.
7	Seasoning	Transformed loan age	PD peaks around year 3-7.
8	Property Type	Dummy for non-core property types, such as hotels.	Non-core property types have higher PD due to higher operating business characteristics.

As shown in Table 2, in addition to loan and property level factors, market-wide factors play a significant role. We use the market vacancy rate as a proxy for the contemporaneous space market condition, the market-wide price change as a proxy for the commercial real estate capital market condition, and the market condition at origination to approximate the average underwriting quality. That is, when the commercial property market is tight and experiences low vacancy rates, myopic lenders tend to loosen underwriting criteria and admit more lower-quality loans than when the property market experiences high vacancy rates.

The other explanation is that these market factors serve as proxies for the option value of borrower equity positions. Given the same DSCR and LTV, when the market is good, the option values of borrower equities tend to be higher (at least from a regular borrower's viewpoint) than when the market is bad. In other words, if the DSCR is 0.8 and LTV is 100%, the troubled borrower is more likely to hold onto the property without defaulting than when the general market condition is favorable, and the same borrower is more likely to default given the same DSCR and LTV then when the prevailing market condition is deteriorating.

In general, for the conditional default probability model, we find that the variables we identify lead to accuracy ratios (AR) of 50% to 60% or more (equivalent to ROC ratios of 75% to 80% or more), both in- and out-of-sample.

### 3.2.3 Modeling Loss Given Default

Loss given default (LGD) measures loss severity if the loan is already in default. When a commercial mortgage is in default, if the lender decides to first take possession of the collateral property and then dispose of it to recover mortgage principal, then the LGD is simply a function of the disposition value of the collateral in relation to the unpaid loan amount plus transaction and administrative cost. The lender may decide to work out and restructure the loan if the expected LGD is too high by taking the foreclosure route, but the decision to restructure largely depends upon the perceived collateral liquidation value. Our LGD model is a sum of two components.

- Loss from principal. This is the loss due to the difference between a collateral property's liquidation value and the face unpaid principal balance of the commercial mortgage.
- Loss due to costs and expenses, including, but not limited to, lost interest, transaction cost, legal and administrative expenses, and property maintenance and renovation cost, etc.

In other words, a commercial mortgage's LGD can be expressed as:

$$LGD_t = g[T_3(LTV_t), Y] \quad (5)$$

where  $T_3$  is a transformation function of LTV to make it linear to  $LGD_t$ ,

$Y$  denotes the empirical variables proxy for disposition costs,

and  $g$  is a linear specification.

From a theoretical standpoint, the principal loss part of a commercial mortgage's LGD is simply the ratio of principal shortfall from collateral liquidation and remaining loan balance, i.e.,

$$LGD_{Principal} = -\frac{Collateral\ Value - Loan\ Amount}{Loan\ Amount} = \frac{1}{LTV} - 1 \quad (6)$$

$LGD_{Principal}$  should be an inverse function of  $LTV$  if the CRE market is efficient, with negligible transaction costs. Because the CRE market is not as efficient and carries significant transaction costs, the liquidation price of distressed commercial properties tends to trade below the market price of comparable non-distressed assets. We find that the degree of distress in the actual loss severities data could be partially proxied by another observable variable: time to liquidation.

Drawing upon a large and updated historical LGD dataset, we can confirm the model's empirical validity. Using actual observable variables, empirical evidence clearly supports the statistical and economic significance of LTV, time to liquidation, and collateral size. Beyond what is explained above, time to liquidation is directly correlated to lost interest, transaction, and property maintenance cost. Collateral size captures the percentage cost of some relatively fixed expenses on the legal and administrative sides. For example, \$1 million legal and administrative cost would add 2% LGD to a \$50 million loan, while the same cost would add 10% LGD to a \$10 million loan. Altogether, our empirical model explains about 50% of the historical loan-level LGD variation.

Table 3 Explanatory variables in the conditional LGD model

No	Category	Measurement	Relationship
1	Loss on Principal	1/LTV	Higher LTV leads to higher LGD.
2	Loss on Interest and property maintenance cost.	Time to resolution (time lag between first missed payment and eventual resolution).	Longer time to resolution leads to higher LGD.
3	Administration and legal cost.	Percentile of the collateral size by property types.	Larger collateral corresponds to slightly lower LGD due to some fixed costs on asset liquidation.

Since the implementation of CMM model uses Monte Carlo simulation techniques, we can simulate numerous future asset income and value paths. These simulated asset values provide a direct measure of loss from principal, thus enabling an LGD measure that is also structurally and causally correlated to the EDF measure.

### 3.2.4 Putting It All Together

In summary, our CMM model applies an asset-based composite approach that combines a structural asset evolution process and empirically calibrated functions for both EDF measures and LGD. The steps to calculate EDF and LGD measures for a given commercial real estate loan include the following.

1. Simulate a large number of asset income paths and values by considering both systematic and idiosyncratic uncertainties.
2. Calculate a series of DSCR, LTV, and other explanatory variables along each simulation path.

3. On each simulation path  $i$ , estimate its conditional EDF and LGD measures at time  $t$ ,  $EDF_{i,t}$  and  $LGD_{i,t}$ , given the simulated realizations of  $DSCR_{i,t}$ ,  $LTV_{i,t}$  and other contemporaneous explanatory variables using Equation 4 and Equation 5.
4. Calculate unconditional EDF measure at time  $t$ ,  $EDF_t$ , by using Equation (1).
5. Calculate unconditional EL at time  $t$ ,  $EL_t$ , using the formula:

$$EL_t = \frac{\sum_{i=1}^N (EDF_{i,t} \times LGD_{i,t})}{N} \quad (7)$$

where  $i$  refers to individual simulation path that has equal probability of asset realization, and  $N$  is the total number of simulation trials. Unconditional LGD at time  $t$ ,  $LGD_t$ , follows by  $LGD_t = EL_t / EDF_t$ .

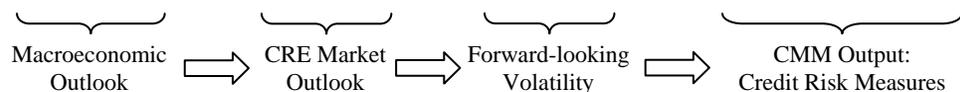
One key benefit of implementing the Monte Carlo simulation technology is the resulting full-range distribution of conditional PD and conditional loss rates through a large number of random draws. Very naturally, from there we obtain all the point estimates regarding UL and various stressed EDF measures and stressed loss rates at any user-specified confidence levels.

### 3.2.5 “What-if” Questions and Scenario Analysis

As our model adopts a strong economically sensible causative specification during each step, it provides users with a powerful and reliable framework in which they can ask “what-if” questions regarding the model’s various inputs and then examine the effects on credit risks of any input changes. For example, a user may be interested in comparing the EDF measures between the baseline economic forecast scenario ( $S_0$ ) and a stressed economic forecast scenario ( $S_1$ ). Furthermore, the user may also want to test the differences of EDF measures if the future CRE market volatility differs from the past, which is a legitimate exercise, given the vast amount of literature pointing to the existence of time-varying volatilities. It would be of tremendous business value to complete the report shown in Table 4 by leveraging CMM as one of the main tools.

Table 4 Scenario analysis over the holding period: an example of model flows

Scenario	Macroeconomic Assumptions	CRE Market Assumptions	CRE Asset Volatility	CRE Portfolio EDF	CRE Portfolio EL
$S_0$ : Base case	$GDP_0$ Unemployment <sub>0</sub> ... ..	NOI growth <sub>0</sub> Value growth <sub>0</sub> ... ..	1.0 times historical market vol	$EDF_0$	$EL_0$
$S_1$ : Stressed case	$GDP_1$ Unemployment <sub>1</sub> ... ..	NOI growth <sub>1</sub> Value growth <sub>1</sub> ... ..	x times historical market vol	$EDF_1$	$EL_1$



Users can change one or all three categories of forward-looking assumptions to conduct scenario analysis. In addition, both macroeconomic and CRE market outlook scenarios can be either direct user inputs or sourced to third-party vendors within the CMM application. In fact, there are a number of third-party vendors who provide forward-looking macroeconomic and CRE market scenarios as fee-based forecasting services. Users may find it cost-effective and informative to take advantage of the available location-specific forecasts from those forecasters. For example, CMM users can use the CRE markets forecasts provided by CBRE Econometric Advisors (EA) and/or macroeconomic forecasts provided by Moody's Economy.com.

Moody's Analytics does not endorse any third-party forecast services nor validates their accuracy. Rather, in absence of a large, publicly traded market for the CRE asset class, we find that the forward-looking views given by industry experts provide useful perspectives, although the eventual market movement may occasionally deviate from their actual forecasts.

## 4 Empirical Data

A model is only as good as the empirical data allows. The shortage of long-term, detailed reliable data poses a major challenge for developing a credit risk model for commercial real estate loans. In the process of developing our model, we assembled a collection of datasets covering different aspects of the CRE asset and loan markets. Collectively, these datasets serve as the foundation for both model development and model validation.

The datasets used in CMM model development and validation provide both aggregate market statistics and property- and loan-level information. Data sources include the following.

- National Council of Real Estate Investment Fiduciaries (NCREIF)—provides aggregate market statistics, mainly capital appreciation, income, and total returns, for five major property types and more than 50 metropolitan areas. Some series are offered at the property subtype levels. Despite some shortcomings, the NCREIF dataset is widely regarded as the industry benchmark measurement in terms of aggregate market movement. The earliest data points go as far back as 1978 in the NCREIF database.
- CB Richard Ellis Econometric Advisors (CBRE EA)—provides aggregate market statistics, mainly market rents and vacancies, at the MSA and submarket (is applicable) levels. CBRE EA market rent data are probably the most well-constructed rent indices, which carefully control for many idiosyncrasies in the actual observed lease rates. The earliest data from CBRE EA goes back to 1980 for office and industrial properties. CBRE EA data also covers multifamily, retail, and hotel property types.
- Real Capital Analytics (RCA)—provides disaggregated property-level transaction data on price and cap rates (if available) for any commercial property transactions valued over \$5 million in the U.S. One can examine the aggregate statistics at any level as long as sufficient transactions exist. This data powers the Moody's/REAL Commercial Property Price Index (CPPI), and the earliest observations begin in 2000.
- Trepp's CMBS Deal Library—one of the largest commercially available databases of the U.S. CMBS universe. The Deal Library contains comprehensive information and history on both individual loans and properties that serve as collateral within the CMBS transactions. Since CMBS is a relatively young segment of the commercial mortgage market, the useful history for empirical research goes back approximately ten years.
- American Council of Life Insurers (ACLI)—publishes periodic reports on the commitment profiles and credit performance of commercial mortgages originated and held by life insurance companies. ACLI data offers the longest aggregate time-series of loan performance spanning several CRE market cycles, beginning in 1965. Hence, this database serves as an invaluable data source for the most credible through-the-cycle analysis for held-for-investment commercial mortgages.
- Federal Deposit Insurance Corporation (FDIC)—publishes quarterly bank-specific reports that detail the holdings and credit performance of banks' loans and leases, including longer-term commercial mortgages and short-term construction loans. Data goes back to 1992, and provides a unique perspective as it is the only public source for the credit performance of the CRE loan portfolios held by banks and savings institutions, the largest players in the CRE lending marketplace.
- Proprietary data contributed by financial institutions—through its business relationships, Moody's obtains proprietary access to historic loan-level data from lenders in the commercial mortgage business. The earliest observations of such datasets go back as far as the 1970s.
- Various published studies and reports, including the series of studies conducted by Snyderman and Esaki et al. The unique importance of the Snyderman-Esaki studies lies in its tabular mortality tables that track individual loan cohorts from cradle-to-grave in terms of default rates. These loan cohorts were originated from 1972 through 1997 by major life insurance companies and experienced 2,700 defaults (15.3%) out of the 17,978 total loans originated. The data is widely used by market participants in benchmarking and in conducting scenario analyses throughout cycles.

While each of the above datasets is indispensable for our model development, none is completely sufficient on its own. We take a mosaic approach that pieces all the information and empirical analysis together within the coherent

overarching framework explained in Section 3. The final CMM model is the result of exhaustive empirical analyses and careful triangulation from complementing insights garnered from multiple data sources.

## 5 Model Validation

Validating a quantitative risk model is both a theoretical and an empirical problem. By theoretical, we refer to the general guidelines of model development, which involve not only academic rigor, but also sound and time-proven business experience. Validation refers to whether or not the model makes econometric sense as well as common business sense, and also whether or not the model specifies an economically-sensible and long-lasting causative relationship that links credit risks with key risk drivers.

Model theoretical validation also involves imposing a parsimonious structure and designing the model so that it is intuitive and simple to understand. A parsimonious structure allows the model to focus on the most important factors while leaving out “accidental” variables that are either redundant or have a one-time transient effect only. Meanwhile, an intuitive model is more traceable and more likely to be used appropriately by regular business users with limited statistical backgrounds. Moreover, a model should be theoretically validated by examining the directional response of PD/LGD to explanatory variables. For example, one would expect PD to increase with the decline of DSCR, and this type of directional relationship can be first validated through a theoretical angle. Finally, common sense and business experience also apply when checking the theoretical reasonableness of model results. For example, since we will not be able to predict *ex ante* which loans will default and which will not default, a model is probably poorly constructed if it consistently outputs PDs in the 95% to 100% range for an input DSCR of 1.0.

Beyond theoretical considerations, a model must be empirically validated, most importantly, through the out-of-sample data. Moody's Analytics has pioneered and refined the use of empirical validation in commercial credit models, and we validate the CMM model using those proven testing processes.

It is useful to consider the model's empirical validation from two separate yet related metrics.

- Model power—the ability of the model to rank-order individual loans from more to less risk. Power describes how well a model discriminates between defaulting (“bad”) and non-defaulting (“good”) loans.
- Model calibration—the consistency of the aggregate-level EDF and LGD measures when compared to the actual realization for a portfolio of loans. It also measures relative risk magnitudes between subsets of a portfolio. For example, whether or not a model can predict correctly if group A has twice the default rates as group B.

These two dimensions are indispensable for a good model, as model power ensures its ability to rank score individual risks, and model calibration ensures the EDF level closely matches the actual default rates throughout portfolios and through time.

For model power, we apply walk-forward, *k*-fold, and cross-validation techniques. These tests include out-of-sample testing (using defaults and non-defaults that were not used in the model development, such as “hold-out” sample) and comparisons to alternative model specifications.

### 5.1 Walk-forward Tests

The walk-forward testing approach allows users to test models and modeling methodologies while controlling for sample and time dependence<sup>5</sup>. It proceeds as follows. We estimate the model up to a certain year and score the observations in the next year. These model scores are out-of-time and out-of-sample. We then re-estimate the model including one more year of data and repeat the analysis for the next year and continue until the end of the sample. For each version of the model, we calculate the accuracy ratio of next year's scores by comparing them to actual realized default rates. Under this approach, we select the development dataset prior to a certain cutoff date, and the validation dataset begins after that date. Multiple tests can be conducted as one moves the cutoff dates backward and forward. This technique reduces the chances of “over-fitted” models, since the testing process never uses data used to fit model parameters. At the same time, the approach allows modelers to take greater advantage of the data by using as much of the information as possible to fit

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<sup>5</sup> See Dwyer and Kocagil (2005).

and to test the models. The results from our out-of-sample tests show a high degree of discriminatory power of CMM model, shown in Table 5.

Table 5 Out-of-sample model power from the walk-forward method

Development Data	Out-of-sample Year	ROC Ratio <sup>6</sup>	Accuracy Ratio
Up to 2006	2007	77.6%	55.2%
Up to 2007	2008	80.8%	61.6%
Up to 2008	2009	78.8%	57.6%

A model is considered to be better than a random guess if the ROC ratio is above 50% and the accuracy ratio is above 0%. A perfect model achieves the maximum possible 100% for both ROC and accuracy ratios.

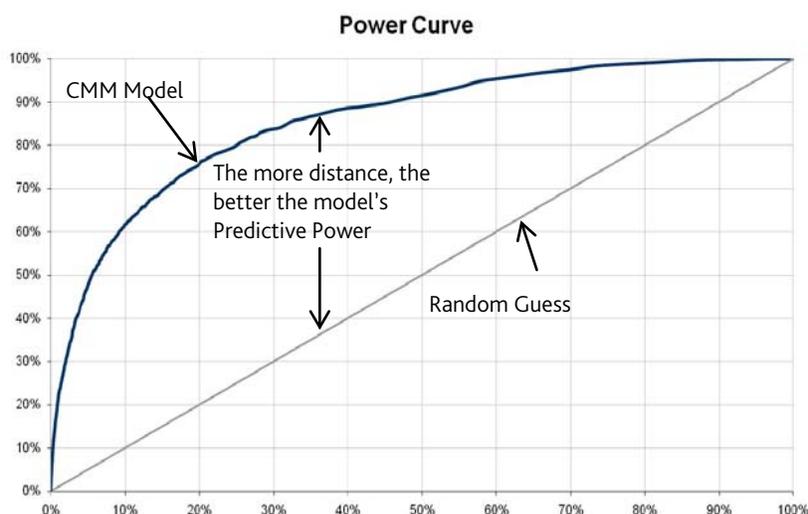


Figure 7 A typical CMM model validation power curve

## 5.2 *k*-fold Tests

Similar results on the model's power can be obtained using alternative validation techniques such as *k*-fold and cross-validation analysis. The *k*-fold analysis tests model stability vis-à-vis different data segments. In this analysis, we divide commercial mortgages into *k* sub-sample (we typically set  $k = 5$ ). We then estimate the model on the sample while excluding the observations in the set  $\{k=1\}$ . This model is used to score the observations in the set  $\{k=1\}$ . Such scores represent true out-of-sample estimates. We repeat this process for each of the *k* sub-samples. Afterward, we combine the out-of-sample scores into one data set and calculate the accuracy ratios and the power curve. We then compare these results with the corresponding in-sample accuracy ratios and power curve. In addition, we check to see whether the parameter estimates for each explanatory variable are stable across the different samples. We find that model performance is well maintained both in- and out-of-sample in the *k*-fold analysis.

As shown in Table 6, our out-of-sample analysis also confirms that the model's discriminatory powers remain consistent across different property types.

<sup>6</sup> The ROC ratio is also commonly called the area under the ROC curve (AUROC), where ROC refers to receiver operating characteristics.

Table 6 Out-of-sample power curves by property types

Property Type	ROC Ratio	Accuracy Ratio
Office	80.8%	61.6%
Retail	81.7%	63.4%
Industrial	79.7%	59.4%
Multifamily	81.8%	63.6%
Hotel	86.8%	73.6%

### 5.3 Validating Model Calibration

In terms of validating model calibration, we conduct a thorough out-of-sample exercise. That is, we first develop a version of the model using the latest default data from the 2000s era and then apply the model to a pseudo-historical commercial mortgage portfolio of the life insurers to compare the modeled PD/LGD to actual realized default rates and loss severities. Since calibration is about the correct overall aggregate levels of the risk measures, we focus on the 10-year cumulative PD values for vintages 1985 through 1995, which we were able to track their credit performance through 2002<sup>7</sup>. The out-of-sample model results match closely with realized defaults, as shown in Table 7 and Figure 8.

Table 7 Out-of-sample comparison of PD levels with actual

Statistical Measure	CMM Model PD	Actual Default Rate
Average	13.0%	13.1%
Standard Deviation	10.4%	9.7%
Minimum	1.9%	0.7%
Maximum	31.0%	27.3%

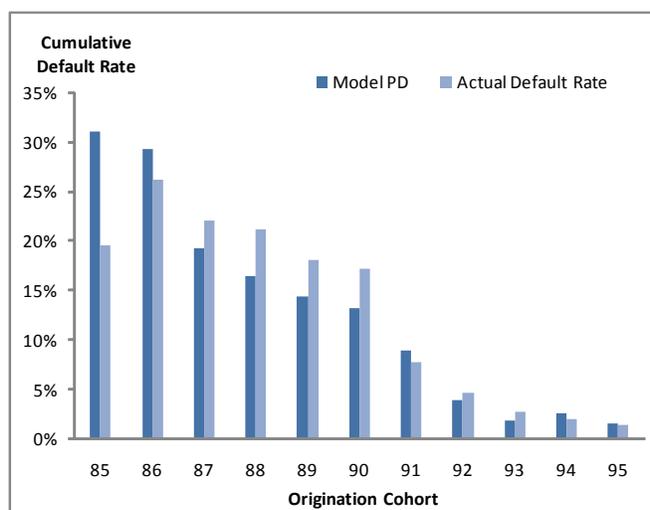


Figure 8 Comparison of the cumulative 10-year model PD and actual, realized default rates

Additional calibration exercises simulate a representative commercial mortgage industry portfolio throughout its history and compare model PD and EL to actual, realized default rates and charge-off rates (proxy for credit losses) using the

<sup>7</sup> See Snyderman (1991) and Esaki and Goldman (2005).

aggregate time-series statistics of the CRE loan portfolios held by FDIC banks. The result also confirms that calibration of model PD, LGD, and EL is largely consistent with banks' historical experience.

Because model calibration also involves relative risk measurements between subsets of a portfolio, we conduct another validation exercise to compare out-of-sample PD level accuracy by buckets. In this exercise, we bucket out-of-sample observations into 30 buckets based on our estimated PD and then compare the average PDs with actual realized default rates for each group, shown in Figure 9. The overall PD levels appear to fit quite well across rating groups based on estimated PD.

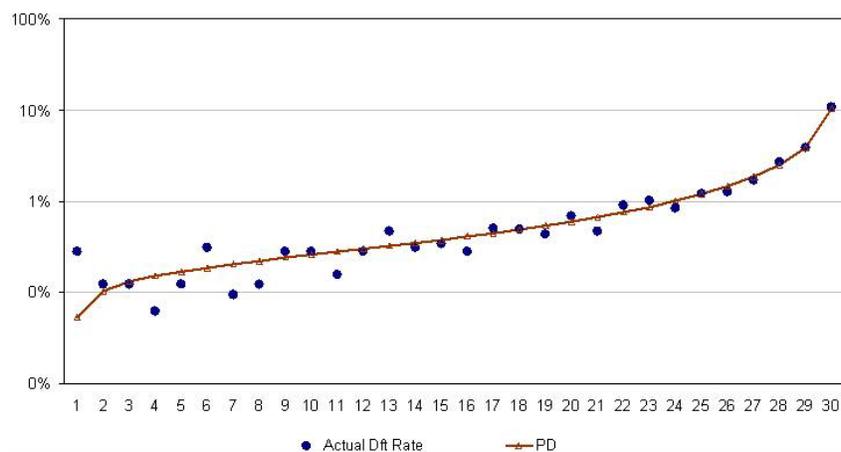


Figure 9 Fitting between PD Buckets and actual realized default rates

Using a variety of validation techniques, we find that the model estimates credit risks reasonably well, conditional upon accurate inputs. We believe that the model produces satisfactory risk measurements over the past several commercial real estate cycles given the empirical evidence we have access to; we also believe that the model is applicable to all the major segments of the market: insurance companies, CMBS, and commercial banks.

The CMM application is flexible enough to allow the user to conduct historical analyses. As a result, users can perform back-testing using an institution's historical portfolios to compare model results to see if they match realized default and loss rates when using the validation metrics from the power, as well as the calibration perspectives. Before users implement the CMM application within their organizations, we encourage them to thoroughly understand and evaluate the model to ensure appropriate use.

## 6 Summary

The commercial real estate and commercial mortgage markets continue to evolve. We have seen numerous changes on many important fronts: demand for commercial real estate space driven by macroeconomic forces, local supplies driven by each MSA's physical layout and zonings, and capital sources increasingly fluid and global in nature. Furthermore, the recent credit crisis has heightened regulatory scrutiny of commercial mortgage lending.

Despite all the changing factors, we find that a commercial property's financials, transpired through DSCR and LTV, continue to play a dominant role in affecting mortgage defaults and losses. Other market-wide factors, such as the prevailing commercial real estate market condition and underwriting pressures, continue to influence the magnitude of point-in-time default rates through their impact on default option values and borrower behaviors. This little-changed relationship between a loan's financial performance and its credit risk makes a quantitative model not only possible, but extremely useful for any serious risk management practice.

After extensive research on a very rich collection of both public and private data sets, we have developed unprecedented insights into the drivers of credit risks of commercial mortgages. The result is our CMM modeling framework, which balances the need for a highly predictive model with a robust, intuitive, transparent, and highly flexible model.

Based on all the evidence seen to date, we firmly believe that our CMM framework will prove indispensable for financial institutions when implementing quantitative credit risk tools in loan origination, portfolio management, scenario analysis, stress testing, and meeting regulatory requirements.



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