# Leveraging Bank Internal Data and Industry Group Data for CECL Modelling

## - C&I and CRE Portfolios

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# CECL Modeling Approach: Strategic and Tactical Considerations

**Tactical Considerations**

- Portfolio materiality
- Data availability: historical and reporting-date data; internal vs. industry group
- Development costs: short-term vs. long-term investments
- Timing constraint, i.e., the remain time till effective date

**Strategic Considerations**

- Invest in data, measurement and system capabilities for both CECL and other business applications
- Consider the impact of less granular quantification on competitiveness
- Consider the impacts on lending and other business decisions
- Coordination and alignment with other processes
- Interactions with various internal and external stakeholders

# Agenda

1. Loss Rate Modeling with Internal and Industry Data
2. Leveraging Bank Internal Ratings for CECL
3. Summary and Discussion

# 1 Loss Rate Modeling

# 1.a

## C&I Portfolios

# Leveraging Industry Data for Loss Rate Modelling

## Moody's Analytics Data Alliance

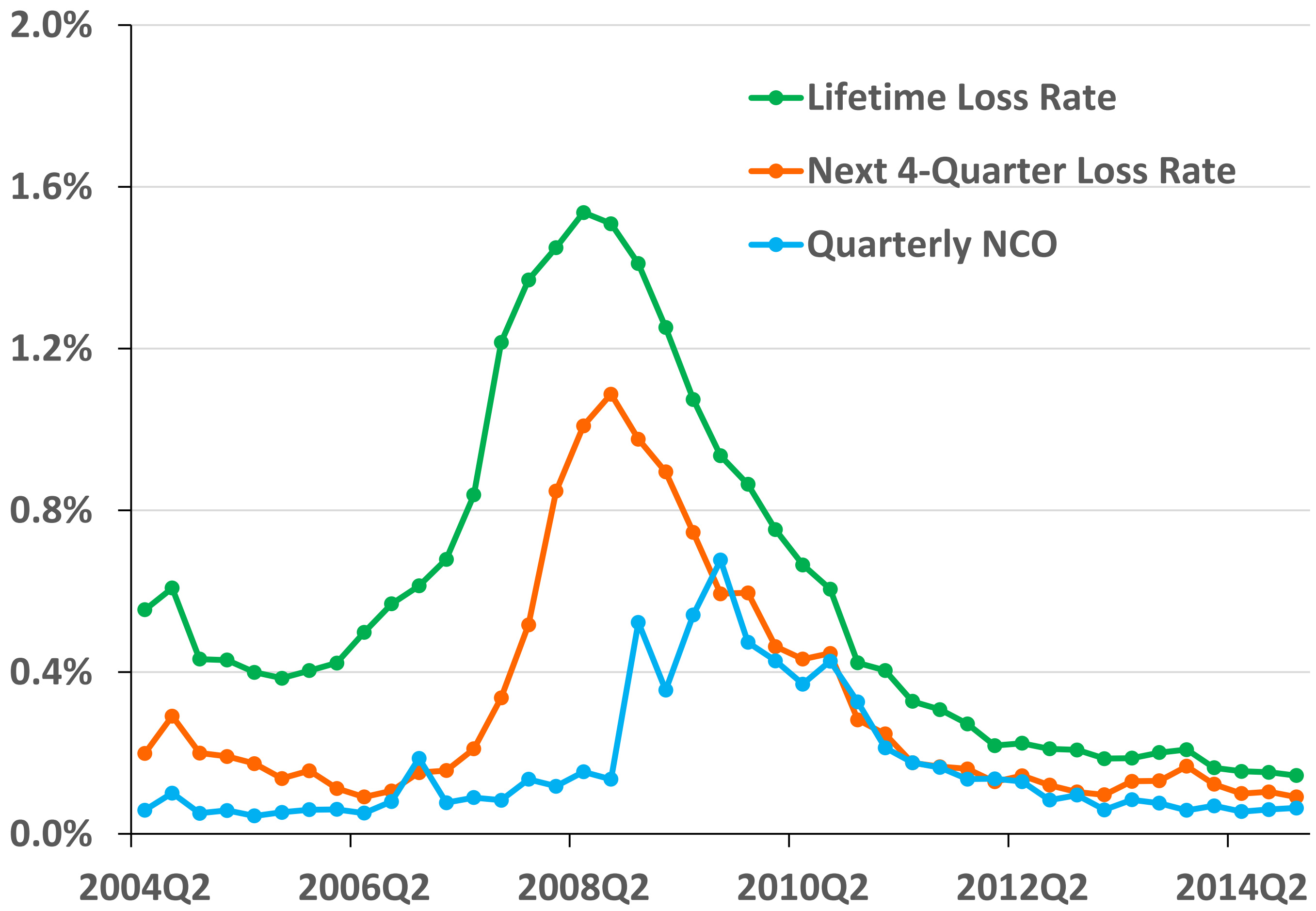
- MA Data Alliance has the world's largest historical time series of private firm middle market loan data for C&I borrowers. There are 19 contributing banks in North America.
  - Contains borrower financial statements, facility and loan information
  - Over 670,000 borrowers, 1.4 million facilities, 20 million entries
  - Facility information: origination date/amount, contractual maturity, unpaid balance, and net charge off (NCO) amounts in each quarter post default for defaulted loans
  - Borrower information: internal rating/PD, industry, geographical info, size, etc.

- The data allows us to track the default, charge off and recovery of each loan through its lifetime, calculating lifetime loss rate at loan, segment, and portfolio levels

# Historical Loss Rate of C&I Portfolio

## Data Alliance Contributing Banks

- 7 million loan snapshots
- Close to 1 million unique loans, 80% of the banks' C&I portfolio
- Quarterly observations from 2004Q3 to 2014Q4
- Segment and portfolio Loss Rates are calculated based on loan balance weights



# Loss Rate Modeling Based on Industry Group Data

» Model lifetime loss rate or quarterly/annual loss rates as a function of loan/pool characteristics as well as macroeconomic scenarios

$$Loss\ Rate = f(tTm, CSAO, loansize, sector, rating, Baa\ Yield, Unemployment)$$

- Time to maturity ($tTm$)= time between as-of date and contractual maturity date
- Credit spread at origination ($CSAO,$ vintage effect) = loan interest rate at origination – benchmark rate
- Loan size = Log10(balance or commitment at origination)
- Sector = {agriculture, health care, transportation…}
- Reporting date credit state = internal or regulatory rating
- US unemployment rate = change in unemployment rate in the next year
- US Baa yield = average Baa yield in the next year

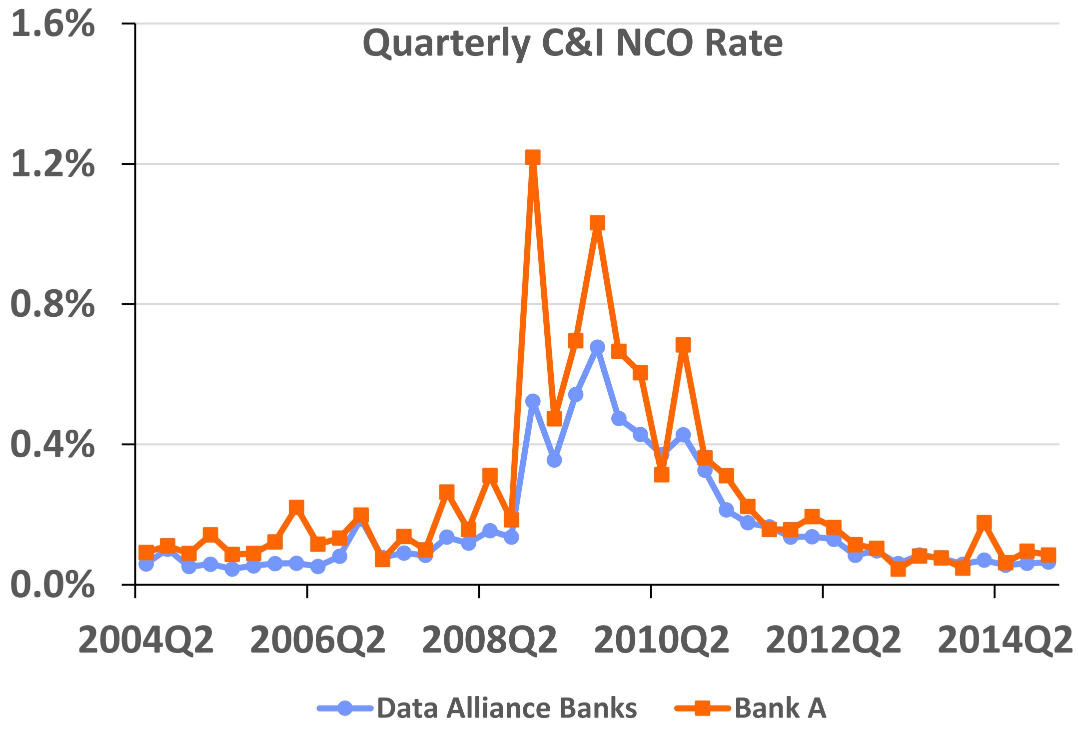
» May still consider Q-factors for additional adjustments for current and future environments that are not captured by the quantitative models

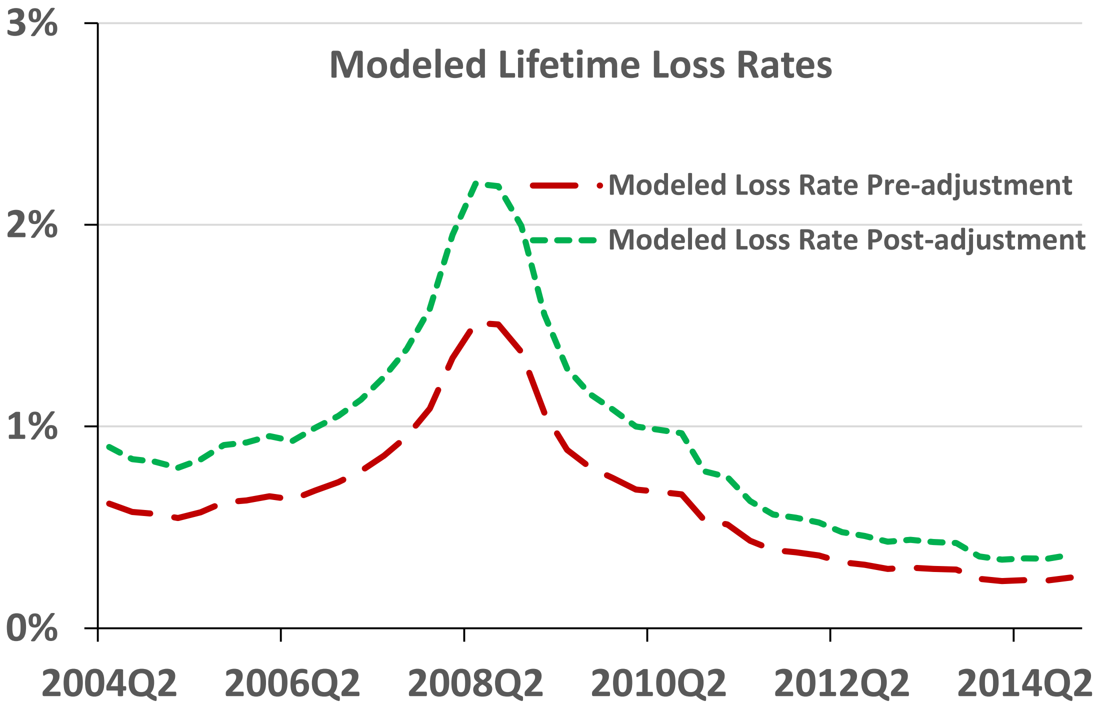
# Incorporating Bank’s Loss Experience (I)

## Example One

» Bank A only has segment level quarterly net charge off rate. Its 10-year average NCO rate is 45% higher than the Data Alliance contributing banks

» A simple multiplier of 1.45 is applied to the model. Different look-back periods can be used to determine the multiplier

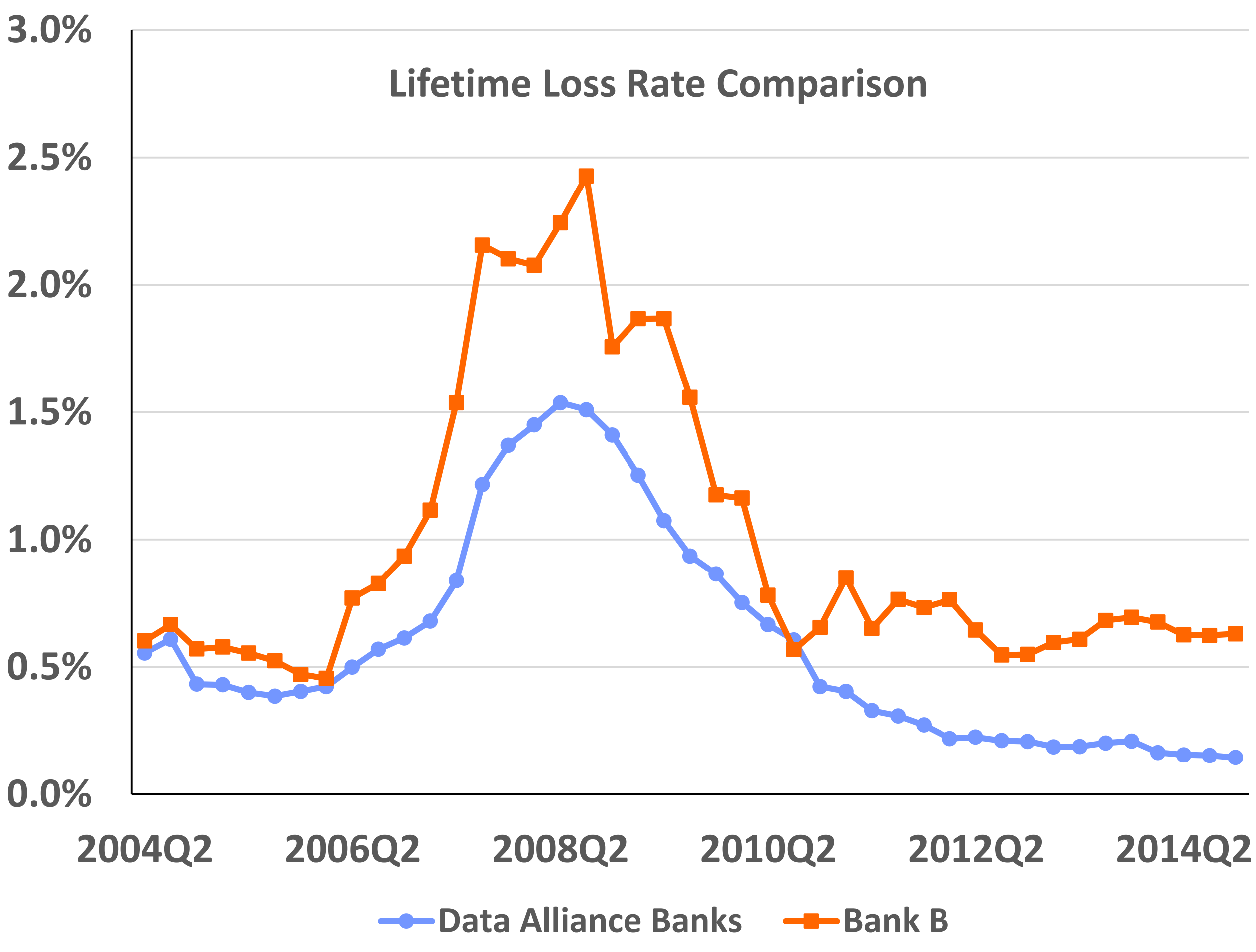


# Incorporating Bank's Loss Experience (II)

## Example Two

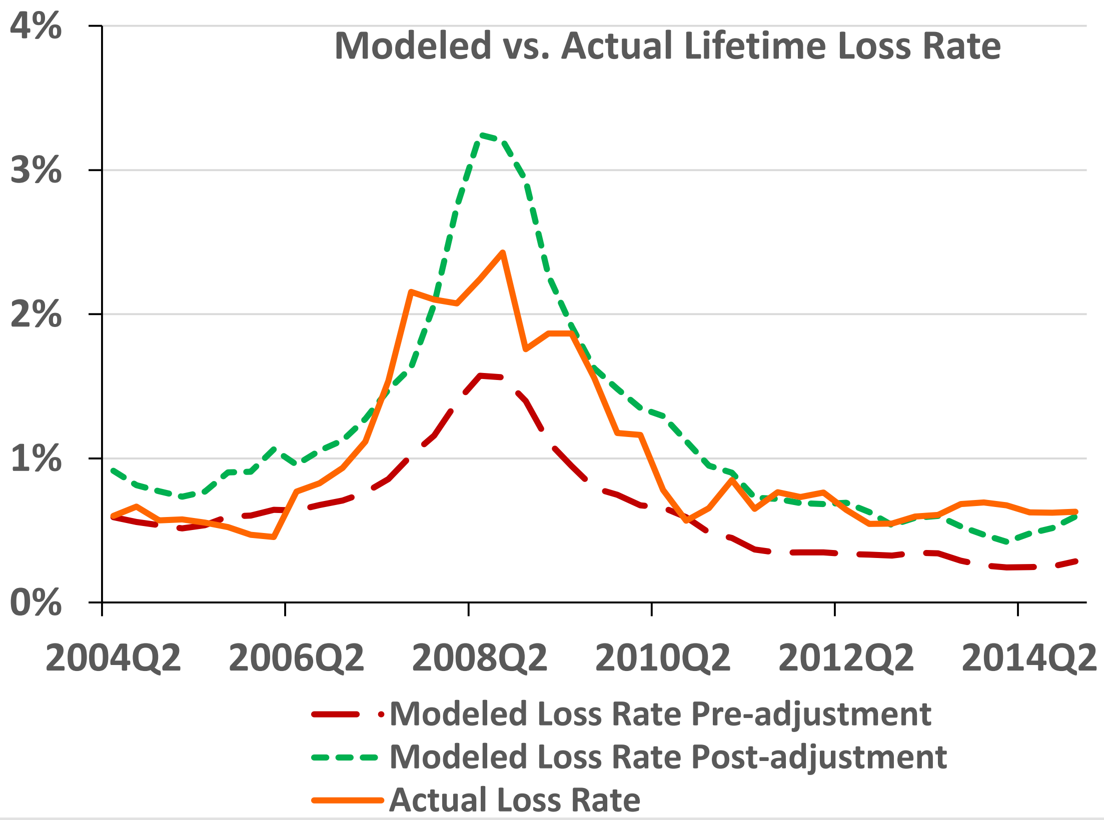
- Bank B has loan level historical data on payments and losses that are needed for lifetime loss rate calculation
- Different level of calibration can be applied by examining loan portfolio loss history and characteristics, relative to industry data
- An examination of Bank B's portfolio shows that the loan size profile of the portfolio differs significantly from the industry peers
- The following slide shows two approaches for adjustments. More granular adjustment could be further applied



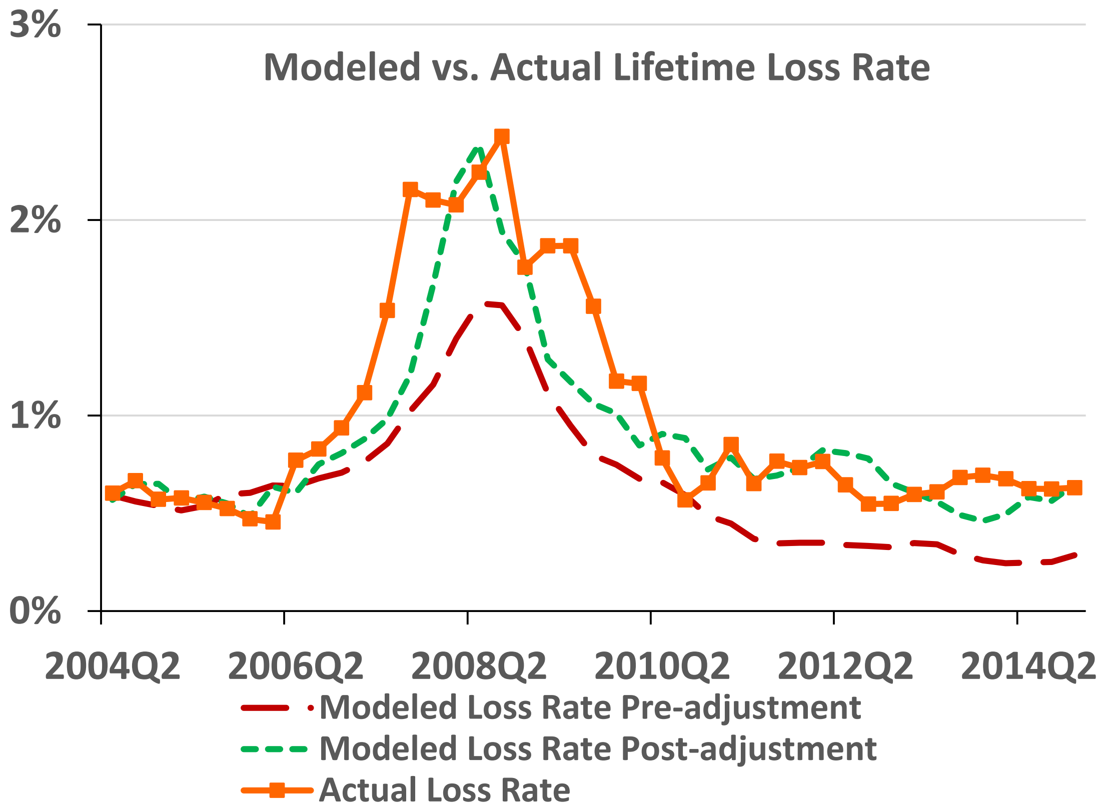
# Incorporating Bank's Loss Experience (III)

## Example Two (Continued)

**Approach 1**: Adjust model sensitivity to loan size




**Approach 2**: Adjust the model sensitivity to both loan balance and economic variables.



# 1.b

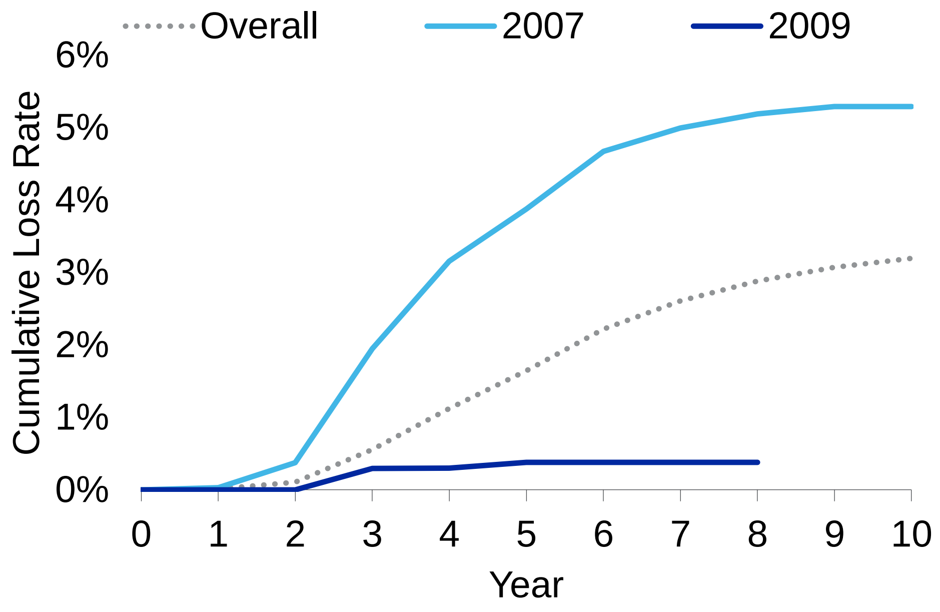
## CRE Portfolios

# Fulfill CECL Requirements for CRE Loans

- Historical experience: Credit loss estimation based historically observed relationship between realized defaults/losses and CRE market cycles
- Current conditions: Current conditions on market, property, and loan
- Reasonable and supportable forecasts: A reasonable forward-looking view into the forecastable future, but no need to go overboard, e.g. 30-year forecast on CRE market condition is likely not supportable

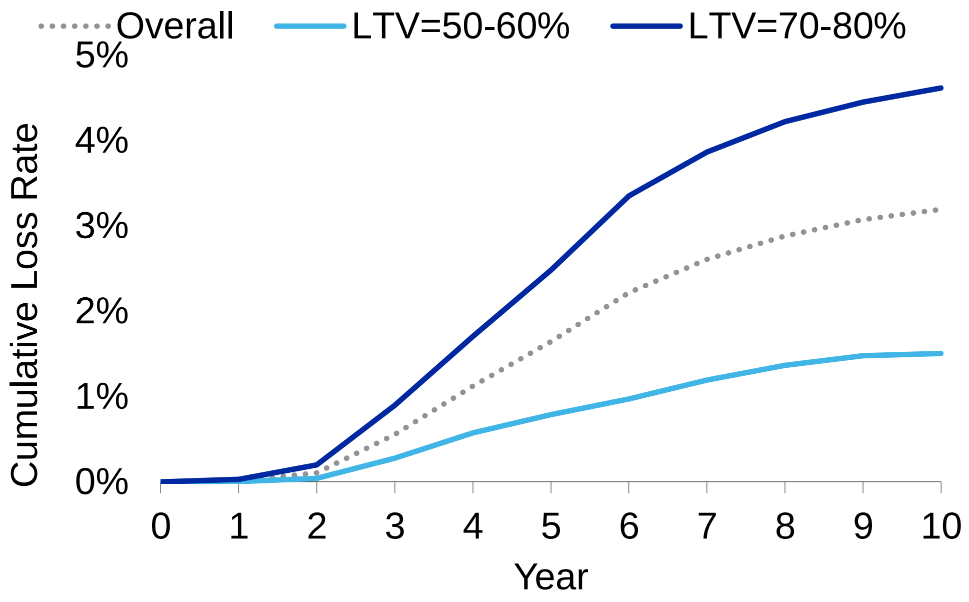
# Historical CRE Loss Experience Is Correlated with Loan Characteristics

» CRE loan performance depends critically on origination vintage




Based on CMM development dataset

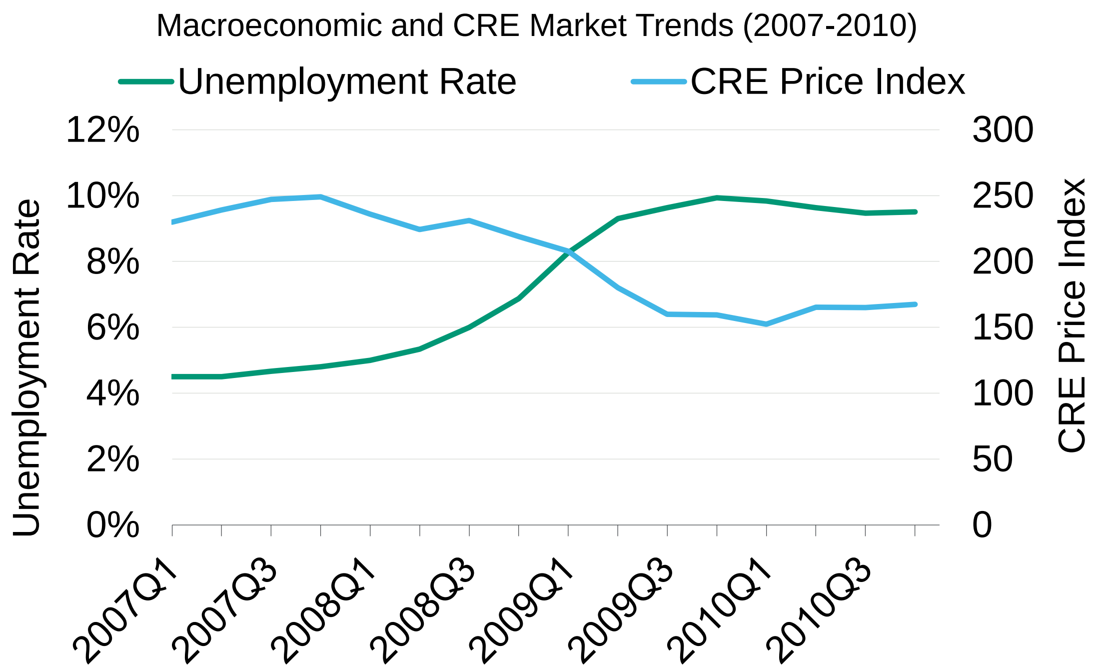
» Origination LTV is a major risk driver for CRE loans

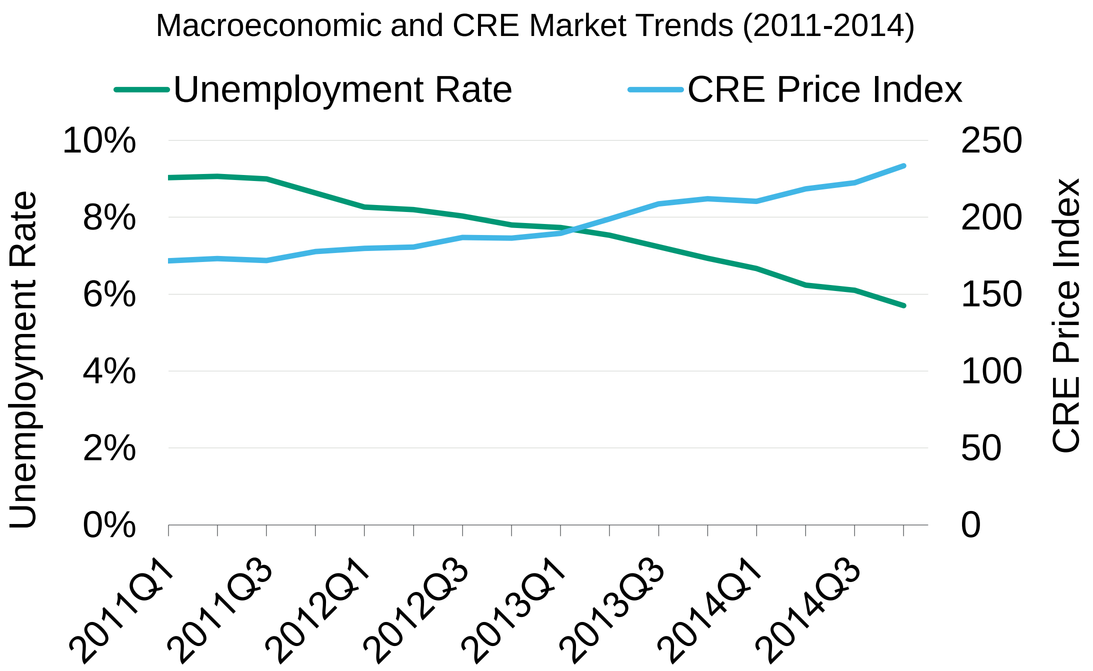



Based on CMM development dataset

# CRE Loss Is Also Driven By Macroeconomic and Market Conditions

- Historical CRE loss is closely tied to historical macroeconomic and CRE market trends
- A reliable CRE loss estimate depends on reasonable and supportable forecasts of future economic and CRE market conditions



# CRE Loss Rate Model Combines Industry Data with Bank Experience

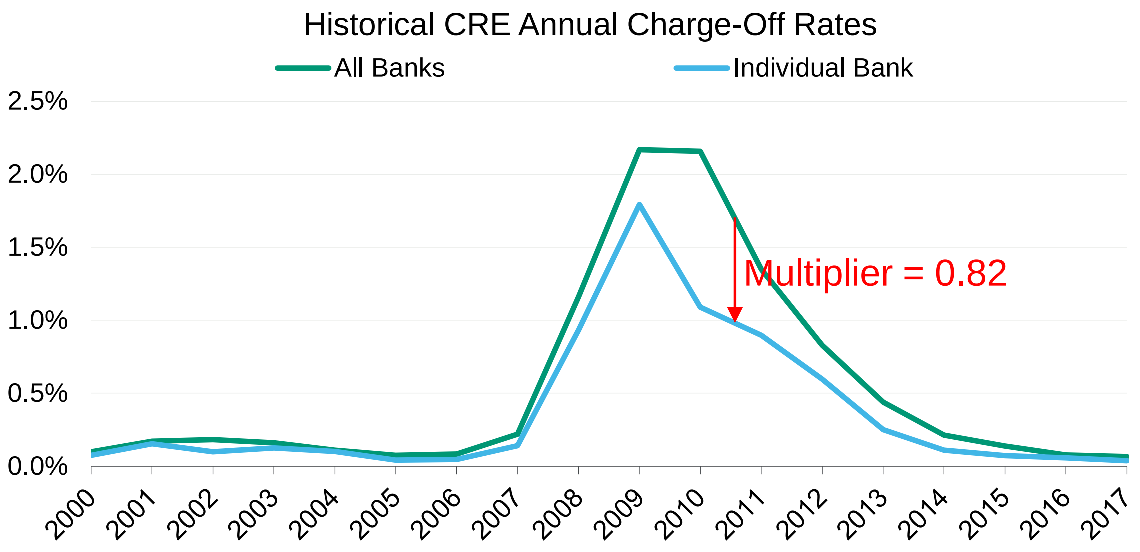
» Model specification: $EL = f(Loan\ Factors, Macro\ Factors, Market\ Factors)$

- Vintage
- Property Type
- Property Status

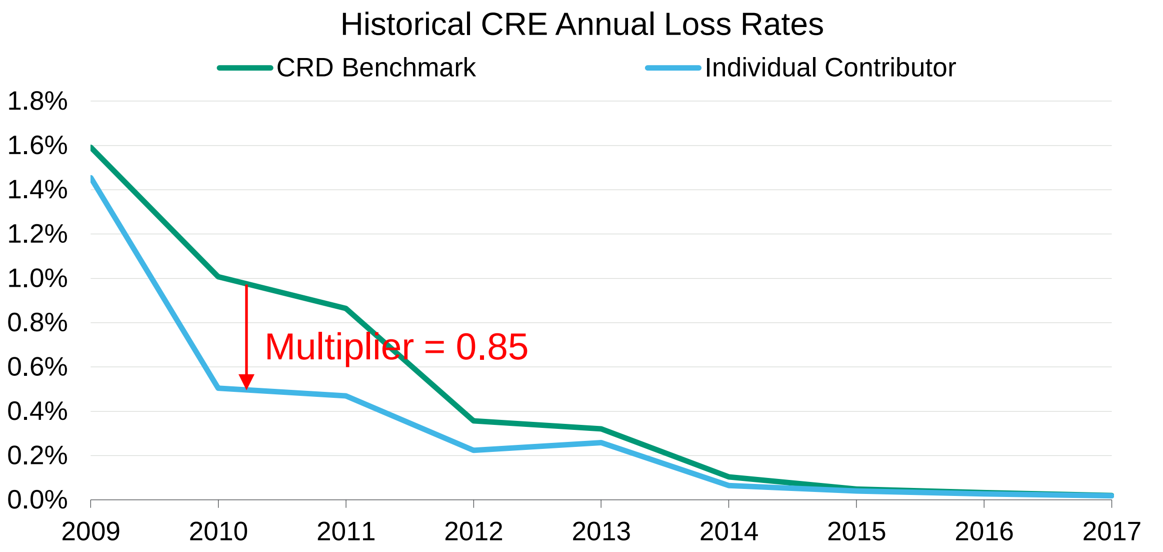
- GDP
- Unemployment
- Interest Rate

- CRE Price Index
- Market Vacancy
- Market Rent

» Final loss estimate can be calibrated to individual bank experience based on call reports

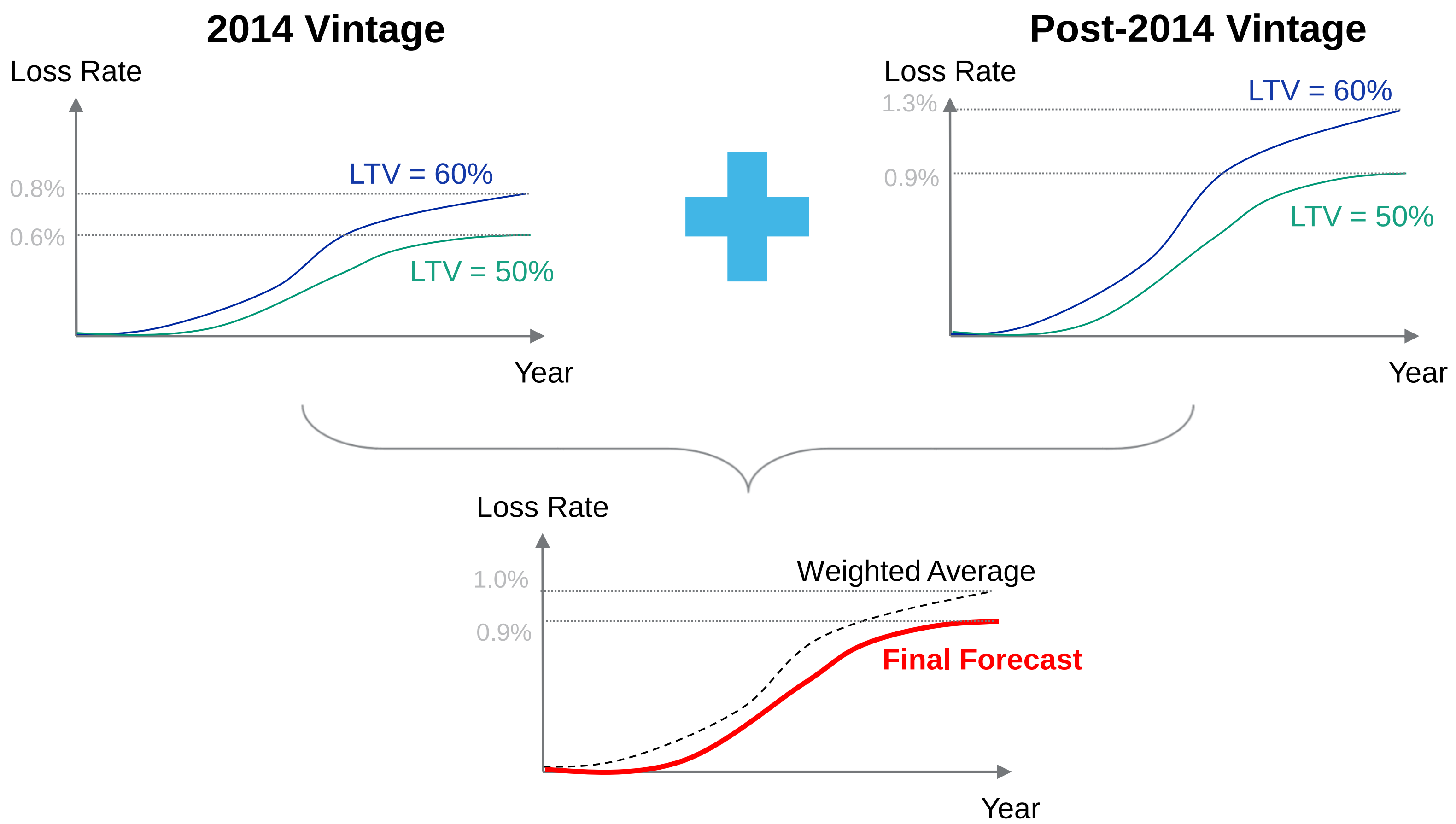



» Alternatively, it can be calibrated to historical loss rate for banks with sufficient historical loss data



# CRE Loss Rate Forecast: An Example

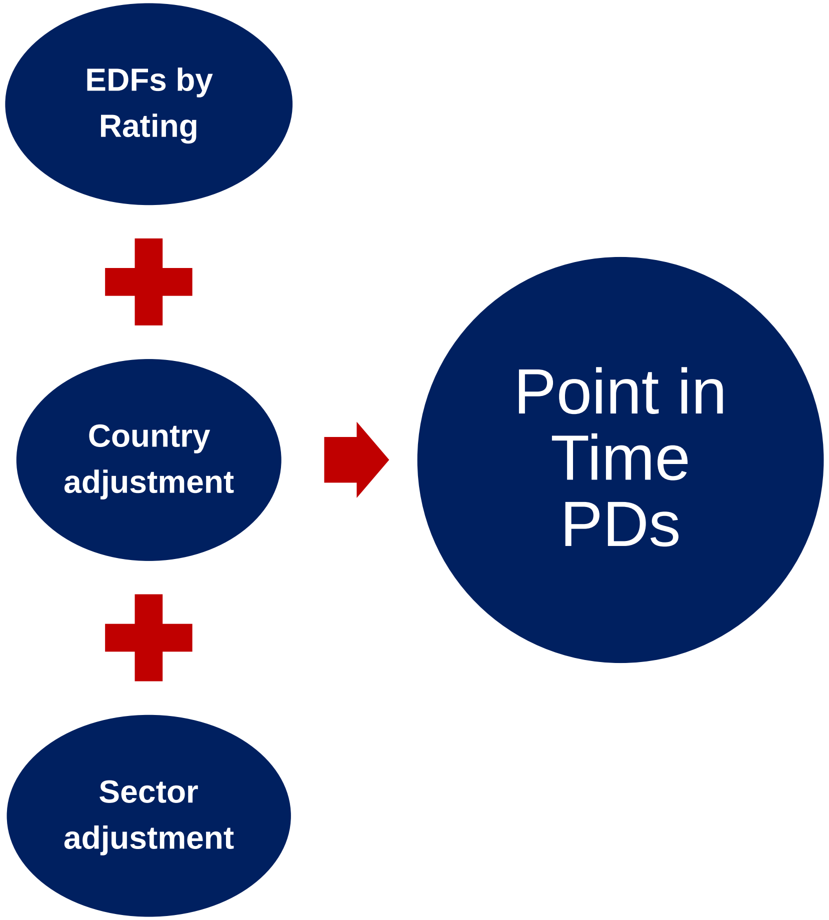
- Suppose that a bank always originates CRE loans at 50% or 60% LTV
- Currently, 20% of its CRE loans were originated in 2014 and the rest were originated after 2014
- Historically, its CRE charge-off rate is 10% lower than that of its peers on average



# 2

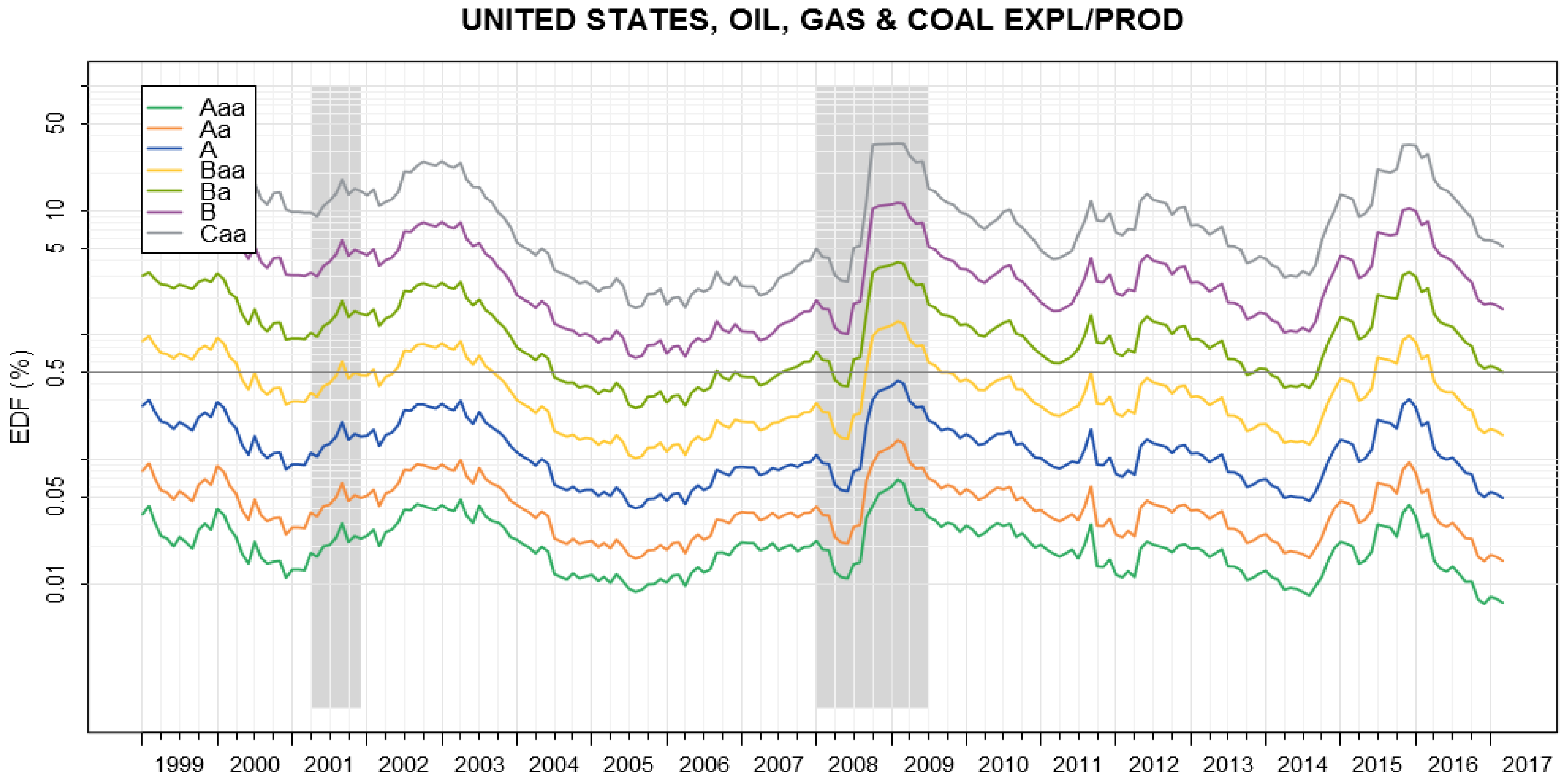
# From Internal Rating to CECL Impairment

# What is the Rating to PD Convertor?

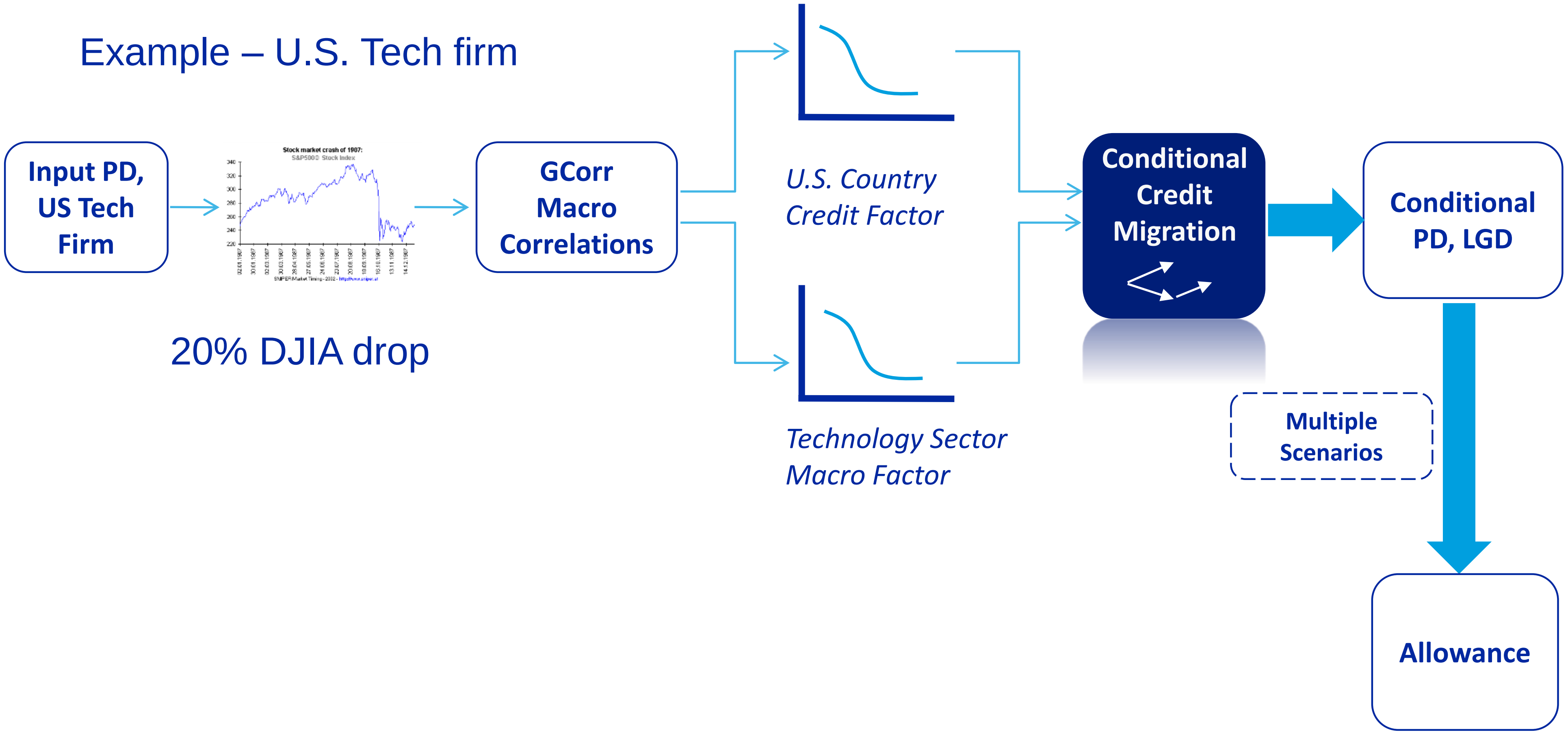



- Use the public firm EDF database to estimate the typical EDF given the rating
- Adjust for sector and country trends
- Use the EDF term structure to generate a Point-in-Time PD term structure
- Can be applied to a financial institution’s internal rating

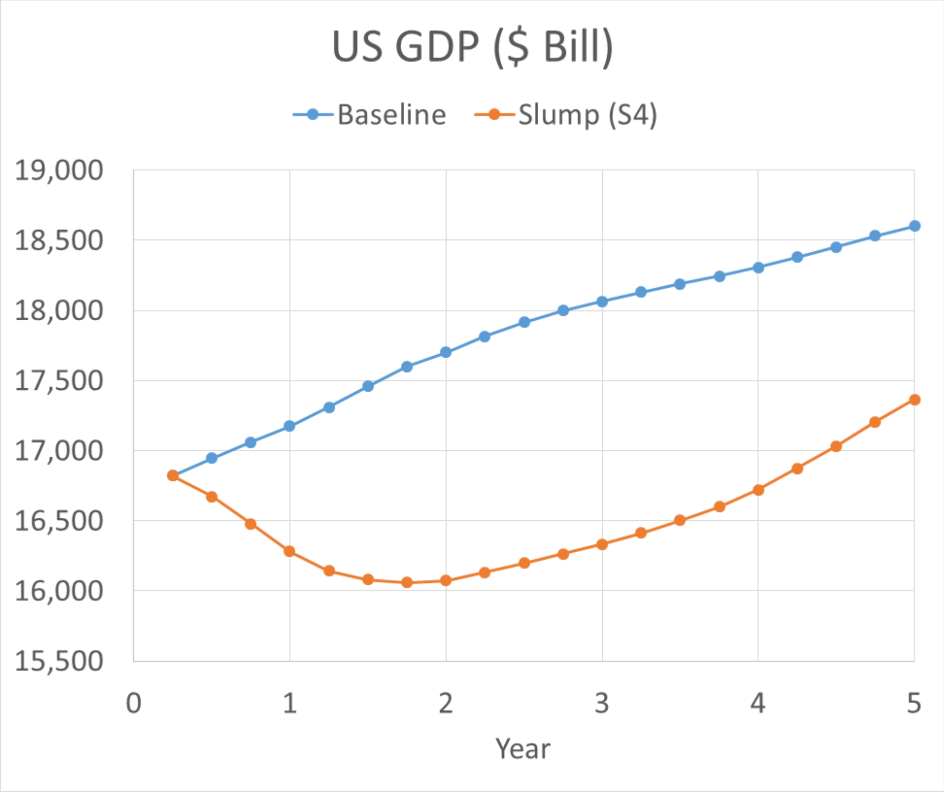
# Ratings Converted into a “Point-in-Time 1-year PD” for a Country Sector Pair

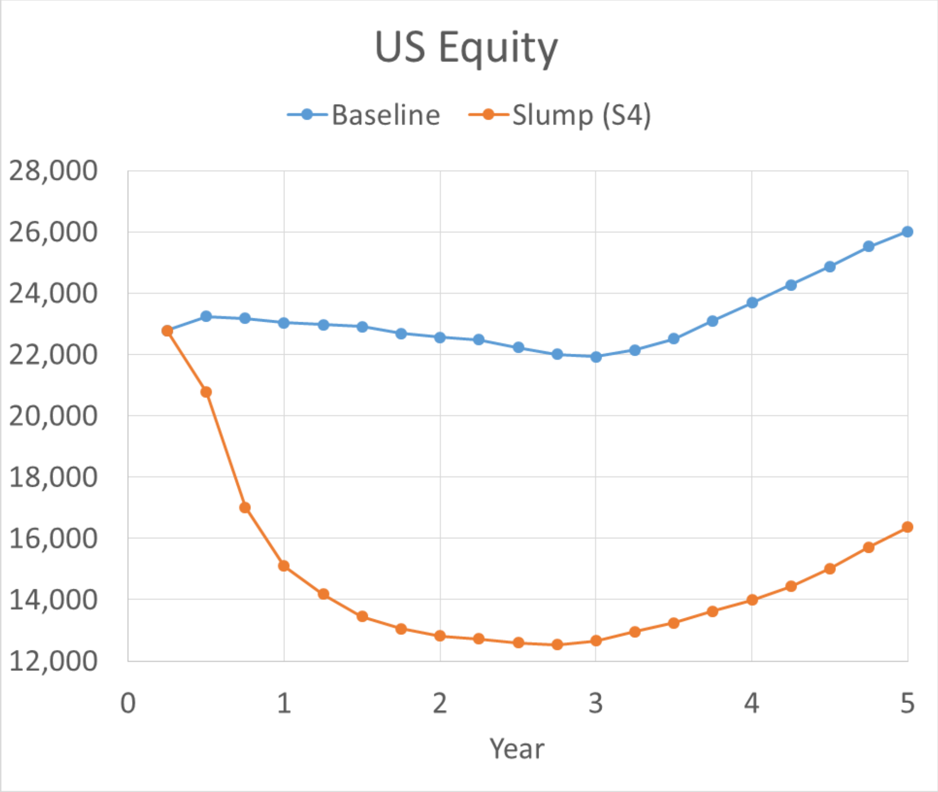


# Scenario Conditioning Through GCorr Macro



# Scenarios for Macroeconomic Variables



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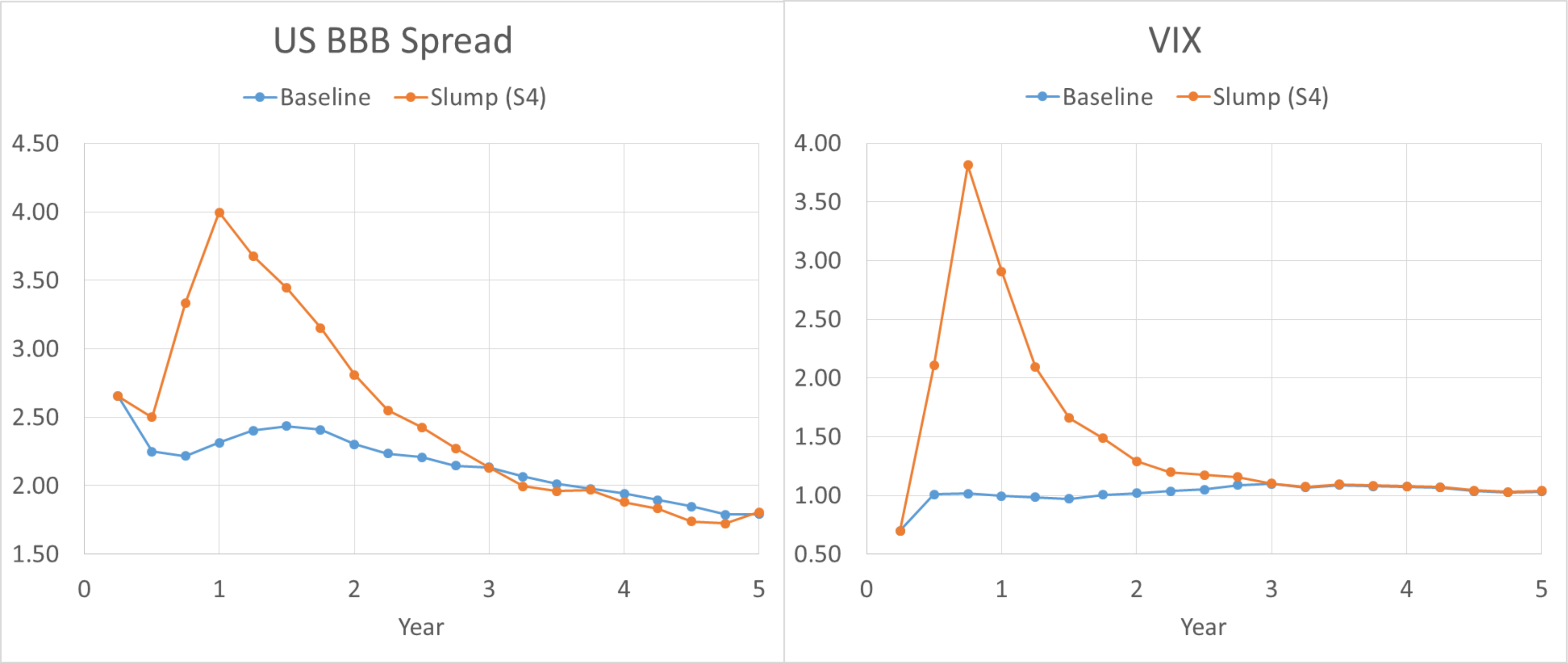
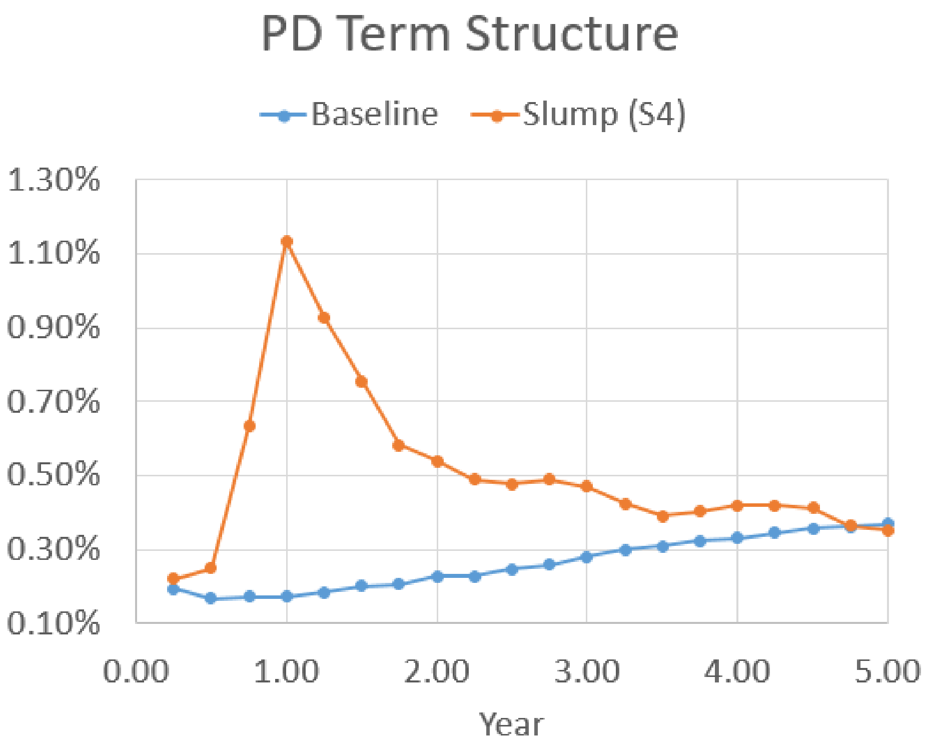


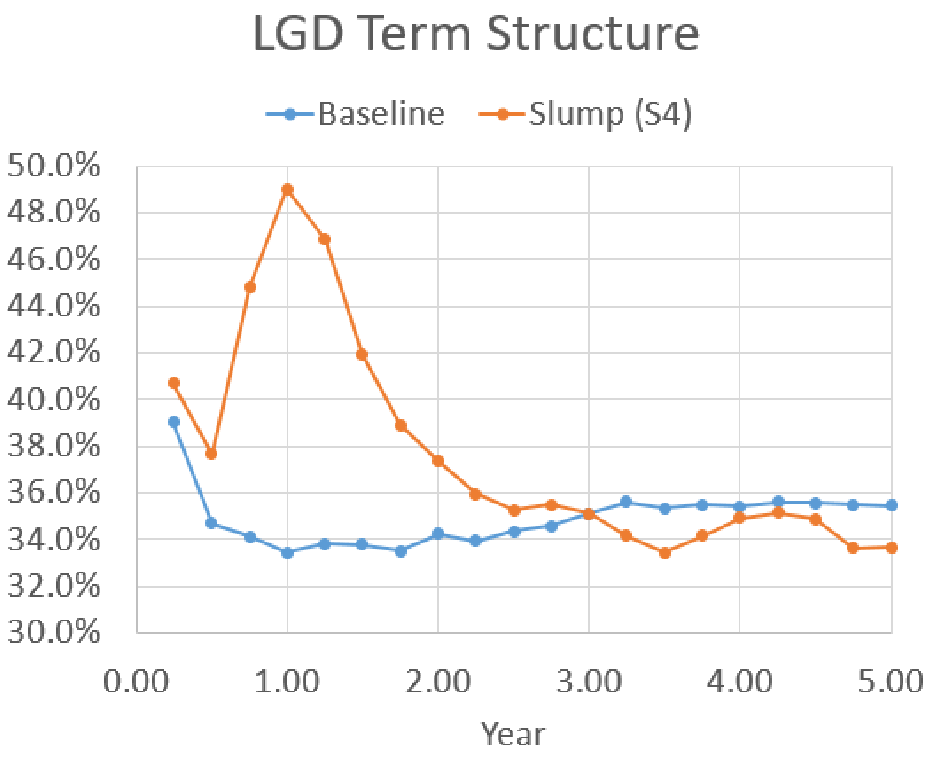
# Example Results

» Loan extended to a US Furniture and Appliances firm

– 5.5 years maturity, Ba2 Rated

– Moody's ECCA Scenarios



# Consistent CRE Model Framework for Loss Rate and Rating-Based Allowance

» Model specification: $EL^{*} = f(Loan\ Factors, Macro\ Factors, Market\ Factors)$

- Vintage
- Property Type
- Property Status

- GDP
- Unemployment
- Interest Rate

- CRE Price Index
- Market Vacancy
- Market Rent

Loan Rating

Local Market Condition

* The dependent variable can also be PD or LGD.

# 3

# Summary and Discussion

# Summary and Discussion

- Institutions often have limited data in loan payment history, default, charge off and recovery
- Industry data has much richer and more granular coverage, and can be leveraged to capture the sensitivity of CECL impairments to various risk drivers
- It is desirable to adapt models built from industry/peer group data to a bank's own experience
- We have discussed ideas and examples in incorporating both bank internal data and industry data for modeling CECL impairments of C&I and CRE portfolios