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# Leveraging Historical Loss Data for CECL


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## Abstract

Collectively, the new requirements for determining Expected Credit Loss (ECL) under FASB ASU 2016-13 (commonly known as CECL) significantly impact community banks, regional banks, and credit unions. Compared to larger banks, these institutions have less experience developing models that forecast losses based on economic scenarios. Regulators have indicated that it is acceptable for these banks to use less complex or model-free methods that rely primarily on historical loss rates to project future, lifetime losses. For institutions that use quantitative models for CECL estimation, historical loss data can be useful for creating reference points or benchmarks that provide perspective for model outputs, and to assist with model calibration, validation, and auditing. The loss information can also be used as the historical experience a bank may revert to past the reasonable and supportable forecast period. The treatment of historical loss information remains a challenge in and of itself. This paper discusses a number of alternative data sources and calculation methods designed to help small financial institutions meet CECL guidelines. We introduce Historical Loss Analyzer (HLA), a toolkit within Moody's Analytics ImpairmentStudio™, and show how to leverage public or internal data of a bank or its peer group to help address CECL requirements.

## Introduction

Community banks, regional banks, and credit unions face significant challenges complying with the requirements of the new accounting standard for estimating loan loss reserves, known as Current Expected Credit Loss ("CECL"). An article in *American Banker* noted that, with a deadline of March 2020, "Recent polls published by vendors and industry groups suggest that more than 50% of community banks have not done anything about CECL except collecting more data in anticipation of needing it."[1]

CECL requires measuring all expected credit losses for financial assets held at the reporting date, based on historical experience, current conditions, and reasonable and supportable forecasts. Large U.S. banks have devoted significant resources to address the new standard, using their experience harvesting historical loan loss data and developing sophisticated models relating losses to economic factors for regulatory stress testing purposes.

While smaller institutions have not achieved the same data sourcing and model development practices, regulators recognize that, since their credit portfolios are less complex, they may be able to comply with less sophisticated methods. The CECL standard allows entities to use judgment when determining relevant information and estimation methods appropriate for their specific circumstances.

Given their relative lack of complexity, rather than relying upon economic forecasts and requiring complex models, these smaller entities are permitted to focus on their historical loss rate experiences, in addition to making judgmental adjustments when developing CECL estimates. Even with these guidelines, however, for some firms there may be insufficient, internal historical data regarding loss experience,  and it may be necessary to use historical industry and peer data. Given the many different ways to treat historical losses, these firms often require guidance as to the best approach. Finally, they may need help developing the infrastructure needed to satisfy regulatory requirements.

This paper explores the CECL standard's background, the choices community banks, regional banks, and credit unions face, and some suggested approaches for dealing with these challenges.

We organize this paper as follows:

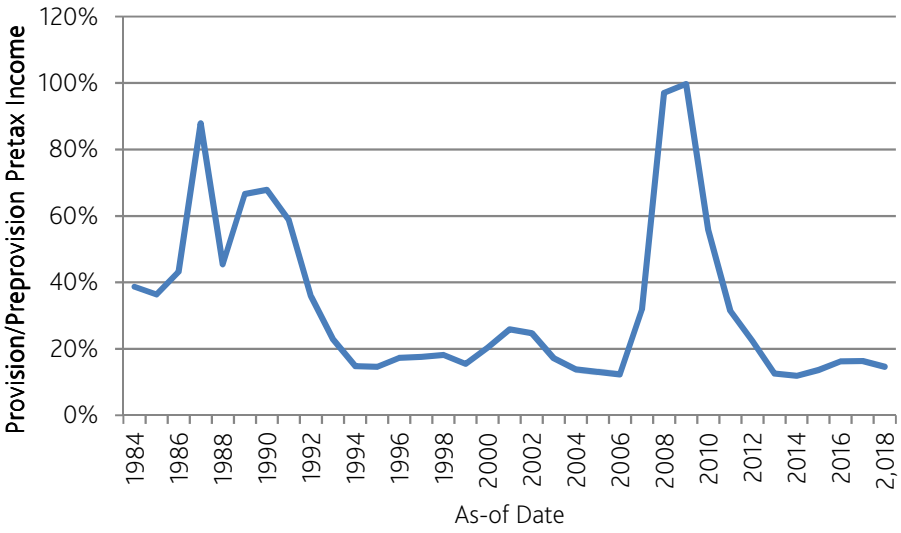
- *Background* provides the background of CECL and its impact on smaller institutions.
- *Historical Loss Analysis* details various approaches for calculating historical lifetime loss rates.
- *Leveraging Different Data Sources* illustrates how public/Moody's data and bank internal data can be used for CECL compliance.
- The last section summarizes.

[1] Cherpack, P. (2019). "Community Banks Still Aren't Ready for CECL," available at https://www.americanbanker.com/opinion/community-banks-still-arent-ready-for-cecl

## Background

During the last 30 years, provisions for credit losses, used to replenish the Allowance for Loans and Leases (ALLL), have averaged a commanding 31% of pre-provision pretax income for FDIC insured banks, ranging between 12% and 100%, shown in Figure 1.[2]

**Figure 1** Provision/Pre-provision Pretax Income (FDIC Data)




Estimating ALLL has always been an area of intense focus for management, shareholders, and regulators. Until recently, banks followed the incurred loss approach for determining ALLL. CECL, the new accounting standard,[3] mandates estimating lifetime losses. This change impacts financial institutions and presents a significant challenge for most smaller banks and credit unions trying to satisfy the associated methodological requirements.[4] [5]

As described in the standard, the estimate of expected credit losses (ECL) under CECL should consider historical information, current information, and reasonable and supportable forecasts of future events and circumstances, as well as prepayment estimates. Financial instruments with similar risk characteristics should be grouped together when estimating ECL. The standard does not prescribe a specific method for estimating credit losses, so its application requires significant judgment. Institutions may utilize various approaches for estimating CECL, including historical loss rates, probability of default/loss given default, roll-rates, and discounted cash flows. Notably, for the period beyond which banks cannot make supportable forecasts, they may revert to historical loss information. For the purposes of this paper, we focus exclusively on historical loss rate methodologies.

For many smaller institutions, the ability to forecast economic conditions beyond one or two years remains highly problematic. While some can take advantage of their economics' department or use forecasts prepared by consulting firms or industry experts, their ability to specifically tie these forecasts to the impact on their portfolio segments through modeling assumptions may be a step they are reluctant to take..

These entities may feel more comfortable making only smaller qualitative judgments, or what are known as "Q factors," in order to reflect their nearer-term assessment of the economic environment's impact on their portfolios. Beyond that, they will be more confident in reverting to historical loss experiences as the main driver of their CECL estimates. The historical loss technique may well be preferred, as it reflects the institution's own experiences, is "model-free," and, while not a "safe-harbor," when alternative forecasts are not supportable, it may be acceptable, assuming proper procedures are followed.

However, even when relying primarily on historical loss experience, many obstacles and questions remain.. These include:

[2] See FDIC Quarterly Bank Profile available at https://www.fdic.gov/bank/analytical/qbp/ .

[3] Financial Accounting Standards Update 2016-13, issued June 2016.

[4] See Tunay, S. (2018). "Impacts of CECL," available at https://www.americanbanker.com/opinion/community-banks-still-arent-ready-for-cecl

[5] See Michael, F. (2018). "The Impacts of CECL: Empirical Assessments and Implications." The New Impairment Model under IFRS 9 and CECL. London: Infopro Digital, 341-369.

- How clean is the historical information?
- What are the impacts of mergers with heritage financial institutions on the data?
- How does the data stack up against industry benchmarks or peer experiences?
- Is the historical period truly reflective of the future or might it be an aberration?
- What are appropriate Q factors?
- How to convert historical loss data to estimates of lifetime losses?
- How sensitive is earnings and earnings volatility to the different approaches pursued?
- How to develop a robust infrastructure so as not to require spreadsheets?

Before describing possible solutions for using external data when internal data is limited, we first lay out some basic calculation alternatives for generating lifetime losses from historical loss data, regardless of the source.

## Historical Loss Analysis

The first step in reviewing an entity's historical loss information is assessing quality. This step includes ensuring that, where possible, portfolios are clearly identified and, if at all feasible, segmented into major categories. These categories include C&I, CRE (income-producing, construction, etc.) and retail (credit card, 1-4 family, auto, etc.). For historical loss information to be meaningful, it should encompass at least one full credit cycle. If the historical data includes results of heritage mergers, the history should be restated to make it as consistent as possible with the present portfolio composition.

Ideally, one should be able to calculate prior historical loss rates for any period *t* if one had the data to associate charge-offs over ensuing periods *t*+1, *t*+2, etc., with the balance at time *t*. The snapshot/open-pool method takes a picture of a loan portfolio at a specific point in time and tracks its performance during subsequent periods until ultimate disposition.

Charge-offs during subsequent periods are aggregated to derive an unadjusted, lifetime historical charge-off rate. A historical lifetime loss series can be constructed and possibly related to prior economic environments and examined as to whether it is applicable for CECL purposes.

Unfortunately, this type of loan-level information may not be available for many entities, and other methods must be explored to construct a historic lifetime loss series.

The primary source of loss information for each portfolio segment is quarterly charge-offs that can be related to loan balances of the quarter. We can utilize historical loss information in a number of ways, depending on the type of information available and assumptions made, to help project lifetime losses.

### AVERAGE QUARTERLY LOSS ANALYSIS

Historical Loss Rates expressed as Quarterly Loss Rate can be calculated by dividing the Net Charge-offs ($NCO_t$) for period *t* by the Outstanding Balance ($Balance_t$) of period *t* and averaging it across *P* quarters:

$$QuaterlyLossRate_t = NetChargeOffs_t / Balance_t$$

$$\overline{QuarterlyLossRate} = \frac{\Sigma_{\tau=t}^{t+P-1} QuarterlyLossRate_\tau}{P}$$

We calculate the lifetime loss rate by simply multiplying the average quarterly loss rate by the remaining life of the portfolio:

$$\overline{LifetimeLossRate} = \overline{QuarterlyLossRate} \times RemainingLife$$

## LIFETIME LOSS ANALYSIS

We can calculate the historical lifetime loss rate for prior periods, if we can make balance run-off assumptions through normal amortization and prepayments

$$LifetimeLossRate_t = \Sigma_{\tau=t}^{\tau+M-1} QuarterlyLossRate_\tau \times BalancePercentage_\tau$$

For example, assume a linear balance run-off as of 2000Q1 over a five-year period with the following quarterly charge-offs information in Figure 2.

**Figure 2** Historical Loss Experience/Balance Profile Example

| Date | 2000Q1 | 2000Q2 | 2000Q3 | 2000Q4 | 2001Q1 | 2001Q2 | ... |
|---|---|---|---|---|---|---|---|
| Balance | $ 56,046,710 | $ 56,581,370 | $ 57,178,805 | $ 56,040,034 | $ 54,913,879 | $ 54,532,094 | ... |
| NCO | $ (5,726) | $ 2,326 | $ (2,746) | $ 9,477 | $ 1,858 | $ 25,008 | ... |
| Quarterly Loss Rate | -0.01% | 0.00% | 0.00% | 0.02% | 0.00% | 0.05% | ... |

Remaining Balance Profile Assumptions

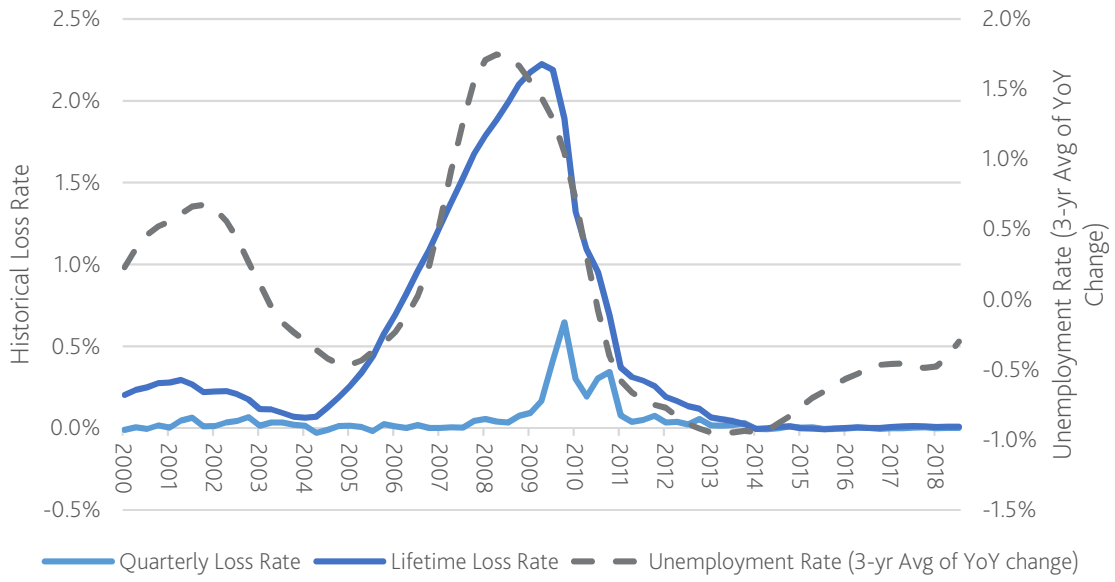
| Term | Q0 | Q1 | Q2 | Q3 | Q4 | Q5 | Q6 | Q7 | Q8 | ... | Q20 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Bal% | 100% | 95% | 90% | 85% | 80% | 75% | 70% | 65% | 60% | ... | 0% |

We can then calculate the lifetime loss rate as of 2000Q1:

$$LifetimeLossRate_{2000Q1} = 100\% \times (-0.01\%) + 95\% \times 0.00\% + \cdots + 5\% \times 0.03\% + 0\% \times 0.01\% = 0.20\%$$

By repeating this calculation for all historical time points, we can develop a time series of historical lifetime loss rates related to various economic indicators, such as unemployment rates, shown in Figure 3.

**Figure 3** Historical Loss Rate vs. Unemployment Rate (transformed)




** Unemployment Rate YoY Change Average in [t-1yr, t+2yr]*

We can also calculate the average lifetime loss rate using this approach:

$$\overline{LifetimeLossRate} = \frac{\Sigma_{\tau=t}^{t+P-1} LifetimeLossRate_{\tau}}{P}$$

### WEIGHTED-AVERAGE REMAINING MATURITY METHOD (WARM)

Similar to the first approach, the WARM method also starts by calculating an average quarterly loss rate. Instead of naively multiplying by the remaining life, the WARM method combines this average quarterly loss rate with balance assumptions:

$$\overline{LifetimeLossRate} = \Sigma_{\tau=t}^{\tau+M-1} \overline{QuarterlyLossRate} \times BalancePercentage_{\tau}$$

Using the same balance profile in Figure 4, an example is constructed to calculate the lifetime loss rates.

**Figure 4** Historical Loss Experience Example

| Date | 2000Q1 | 2000Q2 | 2000Q3 | ... | 2004Q3 | 2004Q4 | ... |
|---|---|---|---|---|---|---|---|
| Balance | $ 56,046,710 | $ 56,581,370 | $ 57,178,805 | ... | $ 55,054,248 | $ 55,584,725 | ... |
| NCO | $ (5,726) | $ 2,326 | $ (2,746) | ... | $ (6,332) | $ 7,616 | ... |
| Quarterly Loss Rate | -0.01% | 0.00% | 0.00% | ... | -0.01% | 0.01% | ... |

Remaining Balance Profile Assumptions

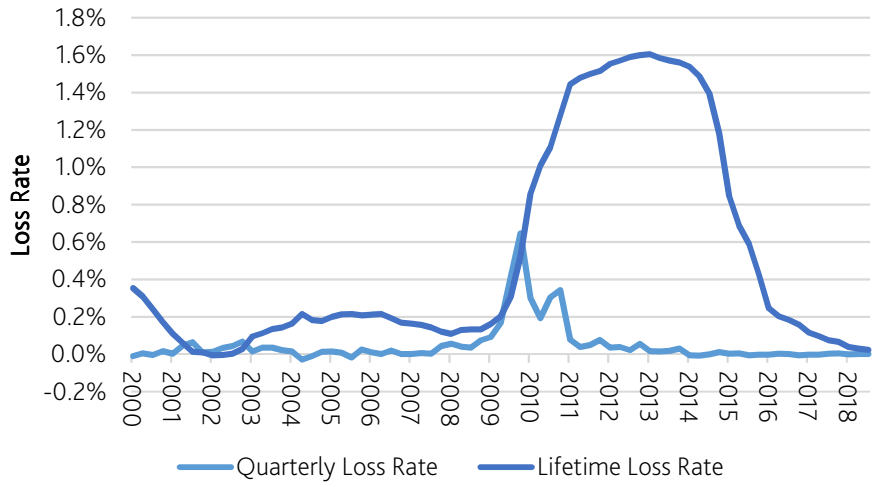
| Term | Q0 | Q1 | Q2 | Q3 | Q4 | Q5 | Q6 | Q7 | Q8 | ... | Q20 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Bal% | 100% | 95% | 90% | 85% | 80% | 75% | 70% | 65% | 60% | ... | 0% |

Assuming the average quarterly loss rate from 2000 – 2004 is 0.02%, we can then calculate the lifetime loss rate as follows:

$$\overline{LifetimeLossRate} = 0.02\% + 95\% \times 0.02\% + \cdots + 5\% \times 0.02\% = 0.20\%$$

By applying the WARM method as of each quarter in history and using five-year rolling windows, results are effectively backward-looking. In practice, however, one can overcome this drawback by selecting the most reasonable and supportable time period to calculate the average quarterly (or annual) loss rate.

**Figure 5** WARM Approach Results Using 5-year Rolling Windows



For both the Historical Lifetime Loss Rate and the Weighted Average Remaining Maturity approaches, we can build a Historical Loss Rate by weighting different periods, where the total weights can differ from 100%. The weights will be applied to quarterly loss rate:

$$QuaterlyLossRate_t = \frac{NetChargeOffs_t}{Balance_t} \times PeriodWeight_t$$

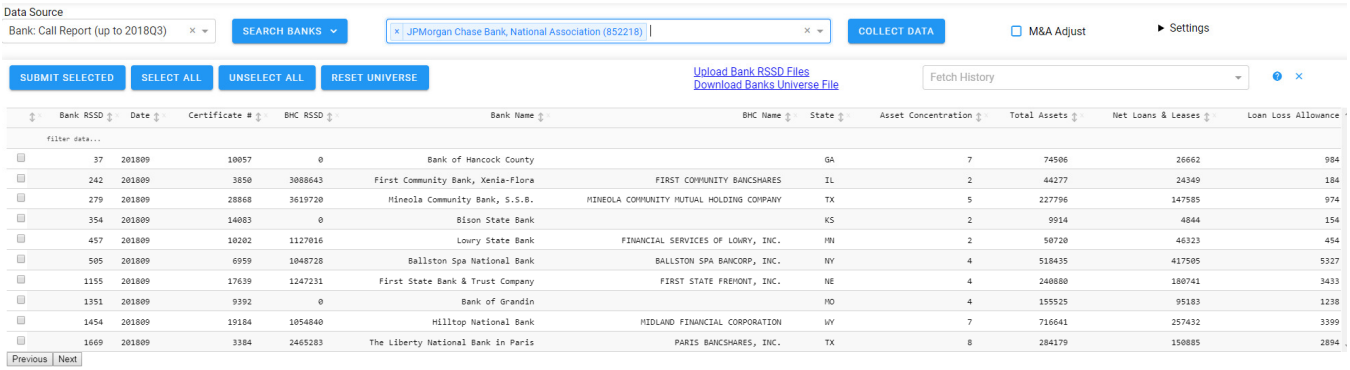
## Leveraging Different Data Sources

As described earlier, internal data may not be readily available, either because its history does not stretch back far enough, it may be confounded by mergers, or it may not be available by desired product segments. Even where internal data is available, public/external data may be a valuable source for benchmark information. It is also important not to rely on spreadsheets but to have a more systematic analytical capabilities that enable quick comparison of various approaches for calculating historical loss rates, blending these with economic factors to make qualitative adjustments, and examining the impacts on an entity's Net Income.

### PUBLIC DATA AND MOODY'S DATA

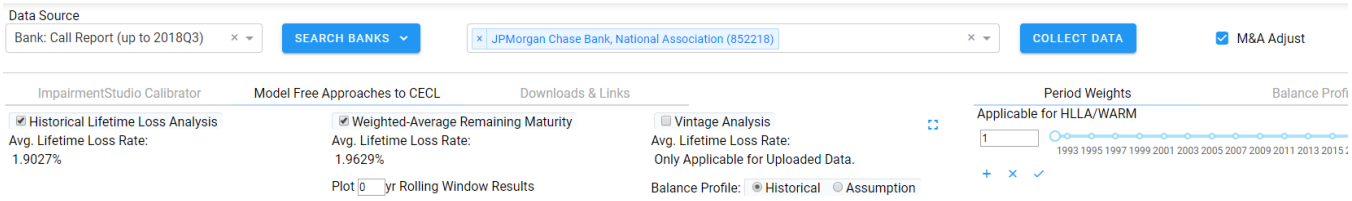
Moody's Analytics has developed a number of tools within the ImpairmentStudio™ Historical Loss Analyzer that help banks develop historical loss information, for either individual institutions or a set of peer banks. Using public data sources such as FDIC Call Reports, Moody's tracks historical merger and acquisition events and processes the data so that the time series data of merged banks have consistent interpretations over time. Using bank call report information or credit union report information, we can easily see associated loss information for user-selected, historical periods.

**Figure 6** Bank Selection Tool



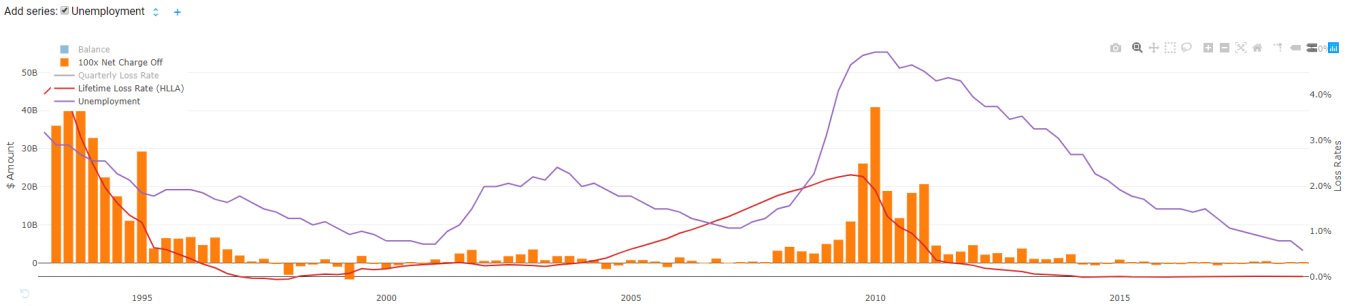

For any individual bank or set of peers, we can develop a historical analysis of losses using any of the approaches and parameters for estimating lifetime losses previously described in the Historical Loss Analysis section.

Figure 7 Lifetime Loss Rate Estimation



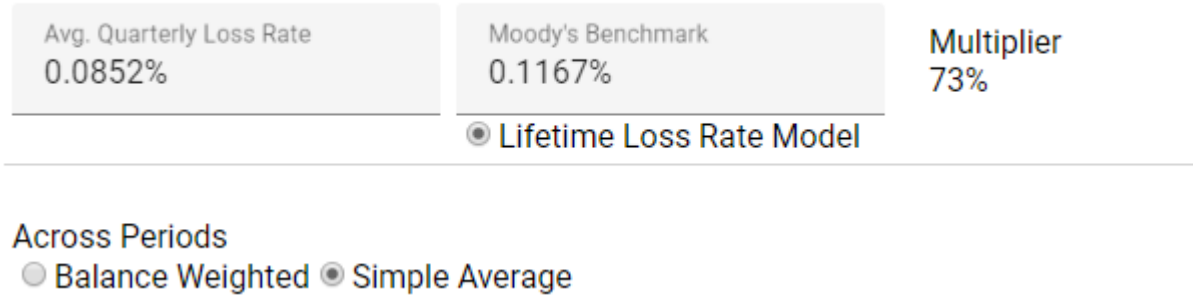

We can merge the historical pattern of lifetime losses together with economic indicator data to get a sense of the environment's impact, as shown in Figure 7. This step can be used to develop qualitative factors when adjusting historical lifetime loss rates.

Figure 8 Visualization of Lifetime Loss Patterns and Macro-Economic Indicators




Moody's Analytics has also developed more sophisticated CECL models within ImpairmentStudio. Loss rates from the Historical Loss Analyzer can be used as a simple calibration mechanism to align Moody's model output for a bank/credit union or its peer group.

Figure 9 ImpairmentStudio Calibrator




In Figure 9, suppose a bank or its peer group's historical average quarterly loss rate of a bank on a particular asset class is 0.0852%, and the historical average quarterly loss rate of the banks, based on whose loan data Moody's model is estimated is 0.1167%. These two figures represent the historical loan performance difference between the bank/peer group and the estimation sample. We can apply the ratio between them, a multiplier of 73%, to the output, when the Moody's model is used on the bank's current portfolio, to reflect the historical difference.

## LEVERAGE BANK INTERNAL DATA THROUGH VINTAGE ANALYSIS

The vintage or year of origination is often an important determining factor for credit losses, especially for consumer portfolios such as credit cards and mortgages. When vintage information is available as part of bank's internal data, more detailed analysis can be performed compared to public data sources.

Assume we have loans with a common vintage v= 2013Q2 and age a = 1,2,3… (expressed either by quarter or year), we can calculate the average quarterly loss rate of each vintage/age combination:

$$\overline{QuarterlyLossRate}_{v,a} = \frac{\Sigma_{i:\, vintage=v\ \&\ age=a} NetChargeOff_i}{\Sigma_{i:\, vintage=v\ \&\ age=a} OriginationBalance_i}$$

This process leads to an upper-triangular matrix and gives us a sense of how the loss experience issued at a particular time evolve by age.

**Figure 10** Historical Loss Rates by Vintage and Age

| | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 201306 | $20,646,560 | 0.013% | 0.004% | -0.070% | 0.016% | -0.024% | 0.020% | -0.019% | 0.043% | -0.039% | 0.022% | 0.099% | 0.015% | -0.014% | 0.000% | 0.003% |
| 201309 | $12,413,295 | 0.021% | 0.011% | 0.016% | -0.010% | -0.005% | 0.005% | 0.038% | -0.022% | 0.002% | -0.001% | 0.005% | 0.002% | -0.004% | 0.019% | |
| 201312 | $40,520,053 | 0.049% | 0.002% | 0.006% | -0.003% | -0.004% | 0.001% | 0.014% | -0.003% | -0.039% | 0.001% | 0.040% | -0.009% | 0.000% | | |
| 201403 | $11,430,498 | 0.022% | -0.014% | -0.004% | 0.012% | 0.009% | 0.045% | -0.017% | 0.002% | 0.060% | -0.036% | -0.012% | 0.026% | | | |
| 201406 | $49,100,783 | 0.009% | 0.006% | 0.004% | 0.037% | -0.010% | -0.026% | 0.001% | 0.009% | 0.022% | -0.016% | -0.010% | | | | |
| 201409 | $10,499,915 | 0.019% | 0.009% | 0.042% | -0.010% | -0.024% | 0.011% | 0.004% | 0.013% | -0.030% | 0.003% | | | | | |
| 201412 | $30,010,262 | 0.004% | 0.036% | -0.008% | 0.010% | -0.031% | 0.001% | 0.008% | -0.008% | 0.009% | | | | | | |
| 201503 | $18,616,498 | 0.014% | 0.027% | -0.032% | 0.049% | 0.005% | 0.007% | -0.019% | -0.001% | | | | | | | |
| 201506 | $42,382,556 | 0.042% | -0.031% | 0.006% | 0.001% | 0.040% | -0.029% | 0.006% | | | | | | | | |
| 201509 | $21,412,656 | 0.018% | -0.006% | 0.033% | -0.014% | -0.002% | 0.023% | | | | | | | | | |
| 201512 | $25,778,843 | 0.050% | 0.003% | 0.037% | -0.007% | -0.001% | | | | | | | | | | |
| 201603 | $18,604,998 | 0.020% | -0.015% | 0.010% | -0.008% | | | | | | | | | | | |
| 201606 | $23,563,920 | 0.009% | 0.026% | -0.022% | | | | | | | | | | | | |
| 201609 | $34,780,327 | 0.012% | 0.004% | | | | | | | | | | | | | |
| 201612 | $7,324,926 | 0.012% | | | | | | | | | | | | | | |

We can average the loss rates across different vintages by age *a* to obtain a historical quarterly loss rate term structure:

$$\overline{QuarterlyLossRate}_a = \frac{\Sigma_{v=2013Q2,\,\ldots} \overline{QuarterlyLossRate}_{v,a}}{\#\ of\ vintage}$$

**Figure 11** Historical Loss Rates Term Structure


Lifetime loss rates can be calculated based on reasonable weight assumptions on different ages:

$$\overline{LifetimeLossRate} = \sum_{a=0}^{M} weight_a \times \overline{QuarterlyLossRate}_a$$

Rather than apply weight assumptions, we can always apply any balance run-off profile to the quarterly term rate structure. In this case, we calculate the quarterly loss rate using the outstanding balance rather than the origination balance. Therefore, the lifetime loss rate will be:

$$\overline{LifetimeLossRate} = \sum_{a=0}^{M} BalancePercentage_a \times weight_a \times \overline{QuarterlyLossRate}_a$$

A more sophisticated approach applies different lifetime loss rates with different remaining lives, based on the historical quarterly loss rate term structure. For example, for a loan with age *a* and maturity *M*:

$$LifetimeLossRate_i = \sum_{a=\alpha}^{M} weight_a \times \overline{QuarterlyLossRate}_a$$

We can calculate the lifetime loss rate of the portfolio by applying the calculation to each loan then aggregate as follows:

$$\overline{LifetimeLossRate} = \frac{\sum_{i=1}^{N} Balance_i \times LifetimeLossRate_i}{\sum_{i=1}^{N} Balance_i}$$

## Summary

Smaller financial institutions face much different constraints meeting CECL reporting requirements. Based on our interpretation, a number of different approaches for evaluating historical loss rate data can be used for estimating lifetime losses, which can then be used as the primary determinant of future losses. By comparing historical periods of loss data with related economic indicators, qualitative adjustments can be made. Especially when internal data is limited or when it is desirable to have external comparative information, the ImpairmentStudio™ Historical Loss Analyzer can evaluate how individual banks or a set of peer banks have performed in the past. These benchmark comparisons can assist banks using model-based approaches to place model outputs in perspective and to assist in model calibration, validation, and auditing.

## References

Michael, F. (2018). "The Impacts of CECL: Empirical Assessments and Implications," The New Impairment Model under IFRS 9 and CECL. London: Infopro Digital, 341-369.

Cherpack, P. (2019). "Community Banks Still Aren't Ready for CECL," American Banker. Available at https://www.americanbanker.com/opinion/community-banks-still-arent-ready-for-cecl

Tunay, S. (2018). "Impacts of CECL," SSRN. Available at https://ssrn.com/abstract=3183416

Financial Accounting Standards Board (2016) "Financial Instruments-Credit Losses (Topic 326): Measurement of Credit Losses on Financial Instruments," FASB Accounting Standards Update.

Financial Accounting Standards Board (2019) "Topic 326, No. 1: Whether The Weighted-Average Remaining Maturity Method Is An Acceptable Method to Estimate Expected Credit Losses," Staff Q&A.

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