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Beyond Theory: A Practical Guide to Using Economic Forecasts for CECL Estimates

Prepared by

Sohini Chowdhury
Sohini.Chowdhury@moodys.com
Director

Cristian deRitis
Cristian.deRitis@moodys.com
Senior Director

Contact Us

Email
help@economy.com

U.S./Canada
+1.866.275.3266

EMEA
+44.20.7772.5454 (London)
+420.224.222.929 (Prague)

Asia/Pacific
+852.3551.3077

All Others
+1.610.235.5299

Web
www.economy.com
www.moodysanalytics.com

Introduction

Starting in 2020, the Current Expected Credit Loss, or CECL, accounting standard will require financial institutions to reserve for estimated lifetime losses on loans and leases as soon as they are originated. CECL will require institutions to take into account reasonable and supportable forecasts as well as information from past events and current conditions. This requirement is a significant departure from the current "incurred loss" generally accepted accounting principles approach, which requires firms to wait until loans reach a probable threshold of loss before adding to their loss reserves. In short, CECL will require institutions to incorporate macroeconomic forecasts formally into their loss allowance estimates for the first time. There are a number of ways in which this can be achieved, as the CECL guidelines do not specify one particular approach. In this paper, we discuss some of the options that institutions have for incorporating economic forecasts into their expected loan loss reserve calculations. We discuss the benefits and costs of each approach and provide practical recommendations based on institution size and complexity.

Beyond Theory: A Practical Guide to Using Economic Forecasts for CECL Estimates

BY SOHINI CHOWDHURY AND CRISTIAN DERITIS

Starting in 2020, the Current Expected Credit Loss, or CECL, accounting standard will require financial institutions to reserve for estimated lifetime losses on loans and leases as soon as they are originated. CECL will require institutions to take into account reasonable and supportable forecasts as well as information from past events and current conditions. This requirement is a significant departure from the current "incurred loss" generally accepted accounting principles approach, which requires firms to wait until loans reach a probable threshold of loss before adding to their loss reserves.

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Reasonable economic forecasts

CECL guidelines require that the economic forecasts that institutions use to estimate lifetime losses are not only consistent with internal managements' forward-looking views but also supportable with sound, quantitative data and methods[1].

An institution can use economic forecasts generated by internal teams or by research agencies or professional forecasters, as long as the forecasts are defensible and consistent with the institution's own views. Consistent with these requirements, Moody's Analytics produces a baseline and alternative forecasts of the global economy[2] every month using a rigorously validated structural econometric model (see Box 1 for a list of these scenarios). The scenarios and their associated probabilities are derived from a simulation of thousands of possible economic outcomes. The distribution of these simulations provides a quantitative foundation to the projection of possible economic outcomes that institutions will use in their CECL processes. For example, Chart 1 shows the forecast of U.S. real GDP growth under some of these alternative scenarios.

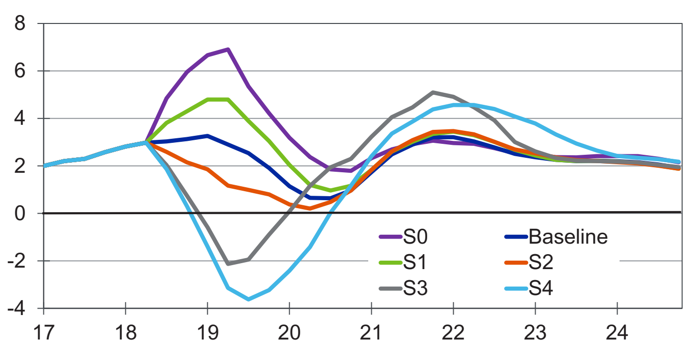
Top-down subnational models transfer these forecasts down to local, state and metropolitan-area levels, ensuring consistency between the national and subnational forecasts. Monthly updates capture the latest historical data and incorporate the latest risks facing the economy to ensure that forecasts are timely and reflect current conditions. Every forecast has an underlying narrative that allows non-economists to understand both the rationale and assumptions behind each scenario.

Incorporating forecasts into loss estimates

Broadly speaking, an institution can account for the forward-looking view of the

Chart 1: Scenarios Cover Range of Outcomes

Real GDP, % change yr ago



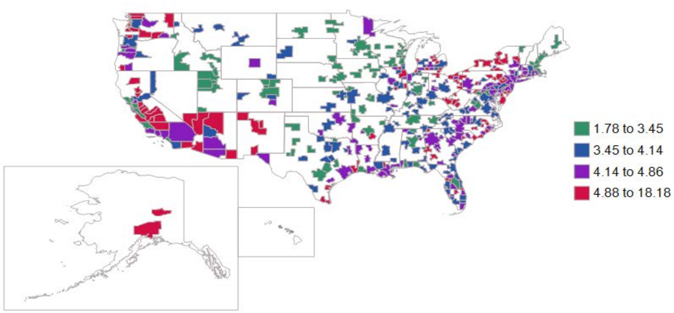
Source: Moody's Analytics

1 See "Economic Scenarios: What's Reasonable and Supportable?" by Cristian deRitis, Moody's Analytics white paper (2017) for what constitutes a reasonable and supportable forecast.

2 See "Moody's Analytics Global Macroeconomic Model Methodology" by Mark Hopkins, Moody's Analytics Regional Financial Review (June 2018) for a description of our global macro model.

Chart 2: Diverse Economic Performance

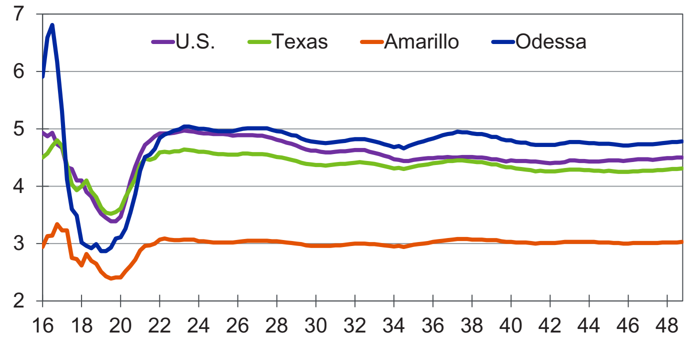
Unemployment rate, %, SA, Jul 2018



Sources: BLS, Moody's Analytics

Chart 3: Not All Regional Outlooks Are Similar

Unemployment rate, %, SA



Source: Moody's Analytics

economy in its credit loss estimates in any one of the following ways, ranked from simple to complex.

- Qualitative Overlay Approach
- Single Scenario Approach
- Shadow Scenario Approach
- Probability-Weighted Multiple Scenario Approach
- Simulation Approach

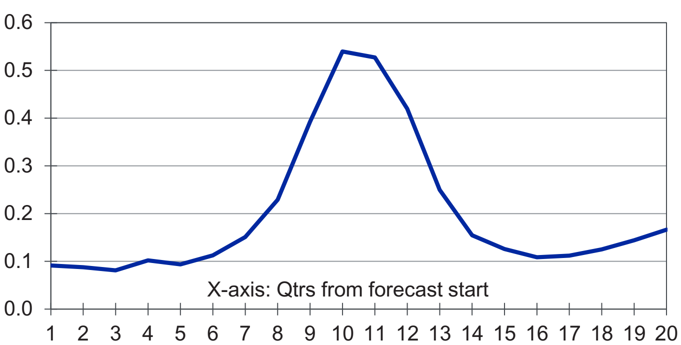
We describe each of these approaches including their respective costs and benefits in the sections that follow.

Qualitative Overlay Approach. In the simplest of approaches, institutions can use forward-looking information to adjust qualitatively their historical loss rates to obtain an estimate for lifetime expected loss. For example, an institution could simply qualitatively increase its historical vintage loss rates to account for higher expected unemployment rates during the remaining life of the loans on its books. While the obvious benefit of this approach is its ease of implementation, the qualitative overlays will need to be defended before regulators and auditors. For institutions with a narrow geographic footprint, basing the qualitative overlays on the local, state or metropolitan area, rather than the national economic outlook, will capture the geography-specific risks and will make this approach more defensible. Chart 2 shows that the unemployment rate is currently ranging from 1.8% in Ames IA to 18.2% in El Centro CA. Clearly the default risk facing banks in each of these local communities varies considerably.

To further emphasize this point, Chart 3 highlights the heterogeneity in the forward-looking forecasts of the unemployment rate in two different metropolitan areas in Texas versus the forecasts at the state and national levels. Given the deviations, a small community bank based in Amarillo will find it more appropriate to tie its expected loss estimates to the future outlook of Amarillo, rather than that of the U.S. or Texas as a whole.

Chart 4: ECL Under Moody's Baseline

Expected credit loss rate, %



Source: Moody's Analytics

Single Scenario Approach. Moving beyond qualitative overlays, institutions may opt to formally calculate their expected losses based on a "most likely" economic outlook—a baseline forecast. The process here would involve the use of a mathematical equation or loss model that explicitly takes economic forecasts as inputs. A very simple example of such a model would be one in which the expected loss in a given month is the product of the probability of default, the loss given default, and the exposure at default corresponding to that month. Mathematically,

$$ECL(t) = PD(t) * LGD(t) * EAD\ (t)$$

PD may be correlated positively with unemployment rate and inversely with GDP growth. The relationship with each of these variables is typically nonlinear such that a small increase in the unemployment rate leads to a large increase in losses but a small decline in the unemployment rate would have a small impact.

The lifetime expected loss corresponding to a scenario 's' is then the sum of the expected loss in each period during the life of the loan. Mathematically this may be expressed as:

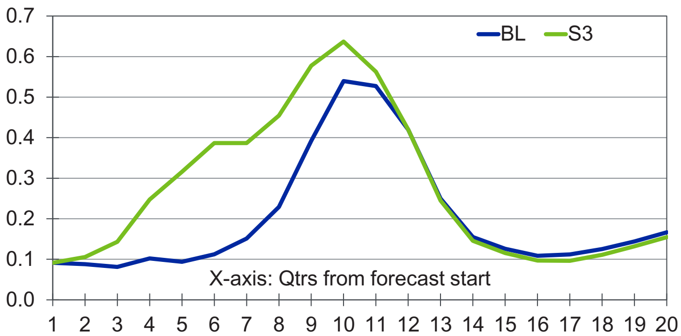
$$ECL(s) = \sum_{t}^{T} PD(t|s) * LGD(t|s) * EAD(t|s)$$

Chart 4 shows the expected loss rates calculated from this model for the Moody's Analytics baseline scenario, assuming zero recoveries.

Although this approach allows information about the economy's future to be incorporated into loss reserves formally through a mathematical model, the use of a single scenario may create complications. First, the use

Chart 5: ECL Under Baseline and Stress

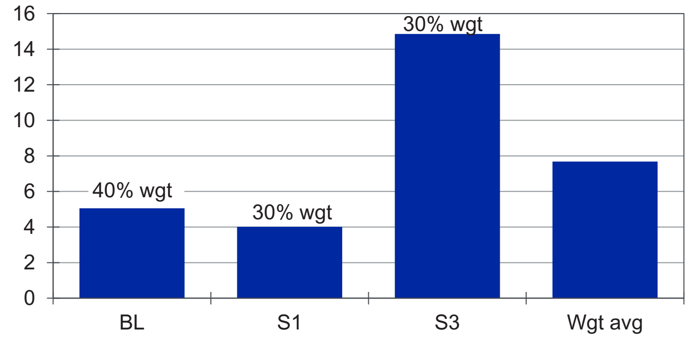
Expected credit loss rate, %



Source: Moody's Analytics

Chart 6: Lifetime ECL Rate

Probability-weighted multiple scenarios, %



Source: Moody's Analytics

of a single scenario assumes perfect foresight in predicting the future state of the economy and does not recognize forecast uncertainty. Second, if indeed the realized path of the economy deviates from the prediction, the baseline outlook will change, causing quarter-to-quarter volatility in loss provisions. Finally, because the single scenario drives the entirety of the expected loss estimate, the choice of the scenario will have to be rigorously defended with auditors and regulators.

Shadow Scenario Approach. One way to formally recognize the aforementioned forecast uncertainty is to estimate losses based on a range of future paths of the economy, including the baseline most likely path. However, since additional scenarios often require additional documentation and may be difficult to manage internally across multiple stakeholders, institutions may choose to adopt a hybrid approach between running a single scenario and running multiple scenarios. Institutions may designate and use one official CECL scenario, but use the loss estimates corresponding to one or more alternative scenarios—that is, "shadow scenarios"—to assess the sensitivity of the losses to varying economic conditions.

Based on these sensitivities, firms can then quantitatively adjust the losses from their official scenario to account for forecast uncertainty. As an example, Chart 5 shows the expected loss rates calculated from the Moody's Analytics 50th percentile baseline scenario (BL) and the 90th percentile downside scenario (S3) using the illustrative expected loss model defined earlier. The extent by which losses in the downside scenario are higher reflects the sensitivity of the institution's expected credit losses to the unemployment rate and GDP growth forecasts. The institution could then adjust upward its CECL estimate from the baseline scenario based on these sensitivities.

The benefits of this approach are that even though the CECL estimates are based on a single scenario, they capture to some extent the uncertainty in macro forecasts and include overlays that are less subjective and therefore more defendable than pure qualitative overlays. The downside is that the approach still involves on-the-top adjustments or overlays, as the forecasts from the multiple scenarios are not incorporated mathematically into the loss estimates.

Probability-Weighted Multiple Scenario Approach. To quantitatively incorporate multiple scenarios in expected loss estimates, institutions may weigh the losses estimated under different economic scenarios by the likelihood of each of the scenarios occurring. The weighted average of these losses would constitute a mathematically determined CECL estimate that incorporates a formal measure of forecast uncertainty. This is the approach that institutions adhering to the International Financial Reporting Standard 9 "IFRS9"—CECL's international counterpart—are required to follow. For institutions also subject to IFRS 9, this is the most sensible approach for CECL, as they can leverage their existing IFRS 9 loss estimation infrastructure.

The biggest advantage of using multiple scenarios is that it controls for the uncertainty associated with a single forecast and mitigates quarter-to-quarter volatility in loss estimates and reserves. However, it also introduces additional complexity. First, running multiple scenarios every quarter-end to estimate loss reserves is considerably more resource-intensive than running a single scenario. Second, institutions will be required to defend the choice of the scenarios and the assigned probability weights since these will have a significant impact on loss provisions.

IFRS 9 requires that institutions use a set of unbiased scenarios, that is, equally weighted upside and downside scenarios. Moody's Analytics produces four scenarios that are equidistant from the baseline scenario that meet the requirements of this rule. These include two upside scenarios (the 4th and 10th percentile) and two symmetric downside scenarios (the 96th and 90th percentile). For institutions using the baseline scenario, and the 10th and 90th percentile scenarios, we recommend a 40-30-30 weighing scheme based on the marginal probabilities of these scenarios and the midpoint between adjacent scenarios[3] (See Box 1 for more information on the derivation of these scenario weights). Chart 6 shows the lifetime expected loss rates calculated from these three scenarios using the same expected loss model defined earlier.

3 "IFRS 9 Probability-Weighted Scenarios" by Martin Janicko, Kamil Kovar, Petr Zemcik, Moody's Analytics white paper (October 2017) describes the method we propose for going from scenario cumulative probabilities to marginal probabilities.

Box 1: Probability Weighted Scenarios

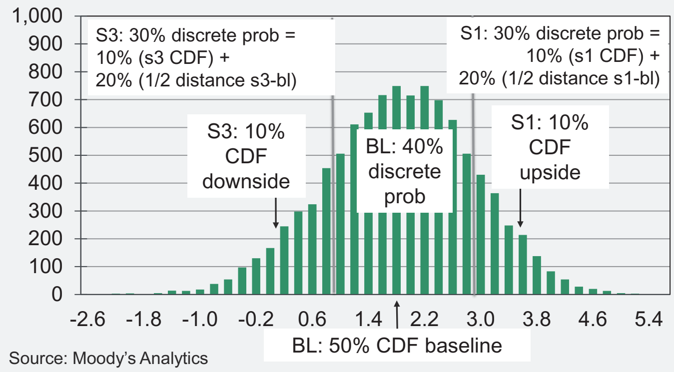
To assist firms with their forecasting exercises and provide a range of possible paths, Moody's Analytics produces a variety of alternative economic scenarios every month. Thousands of simulations are run on an annual basis to calibrate the probabilities for each of the six standard scenarios that are stored in our databases—commonly referred to as Baseline, S0, S1, S2, S3 and S4. The scenarios are selected so as to correspond to a fixed probability of occurrence as shown below.

Scenario	Description	Percentiles
Scenario 0 (S0)	Very Strong Near-Term Growth	4%
Scenario 1 (S1)	Stronger Near-Term Growth	10%
Baseline (BL)	Baseline	50%
Scenario 2 (S2)	Slower Near-Term Growth	75%
Scenario 3 (S3)	Moderate Recession	90%
Scenario 4 (S4)	Protracted Slump	96%

Note that the reported scenario probabilities are cumulative. That is, they measure the likelihood of the economy performing better or worse than the given scenario (that is, cumulative probabilities to the left or to right of the distribution). For users who need to run a discrete number of scenarios (for example, three) and then weight the results from each scenario to derive a weighted average, we propose the following method, shown in Chart 10, for computing probabilities for a set of scenarios.

Chart 10: Assigning Prob. Wgts to Scenarios

GDP growth %, annualized avg, 10k simulations over a 5-yr period



Source: Moody's Analytics

Suppose we wish to run three scenarios (S1, BL, S3). We find the intermediate point between two adjacent scenarios as follows:

Probability of S1 = Cumulative Probability to Left of S1 + (Distance Between Baseline and S1) / 2 = 10% + (50% - 10%) / 2 = 30%.

Probability of S3 = Cumulative Probability to Right of S3 + (Distance Between Baseline and S3) / 2 = 10% + (90% - 50%) / 2 = 30%.

The Baseline gets the residual probability of 100%-30%-30% or 40%, ensuring that the discrete probabilities add to 100%.

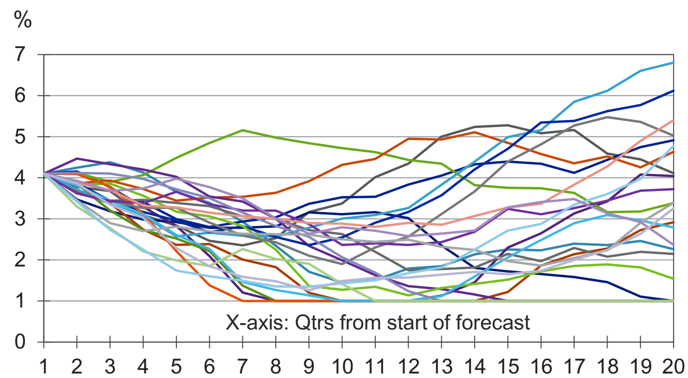
One key assumption baked into this approach is that the scenario weights are derived from a rank ordering of scenario severity that is based on a single variable—the unemployment rate in this case. This is necessary, as it is impossible to rank the severity of scenarios based on the full joint distribution of multiple variables. We must choose a single metric to line up the scenarios from best to worst. Although the use of the unemployment rate is a reasonable and fully justifiable approach, this single metric might not necessarily represent or correlate perfectly with an institution's losses for a particular asset class. For example, for an institution with a disproportionate exposure to residential mortgage lending, assigning probability weights to scenarios based on the distribution of house prices may be more appropriate than assigning weights based on GDP growth or unemployment rate.

For most asset classes, we find that the correlation between the unemployment rate and other key economic drivers driving credit losses is sufficiently strong to be both reasonable and supportable. Nonetheless, it is a topic worthy of consideration. Institutions may decide to weight the results from alternative scenarios differently based on their own unique portfolio characteristics.

Simulation Approach. While the multiple scenario approach is much more robust relative to the single scenario approach, it still only considers a handful of possible future paths of the economy and weighs them based on some likelihood of occurrence. A simulation of the macroeconomic model, on the other hand, will theoretically generate thousands of future paths of the economy for every macroeconomic variable in the model. Theoretically, the average losses resulting from a calculation on each of these simulated macroeconomic forecasts will be the theoretically most accurate estimate of expected losses.

To illustrate this point, we generated a set of 1000 simulations using a simplified macroeconomic model. Chart 7 shows 25 of the

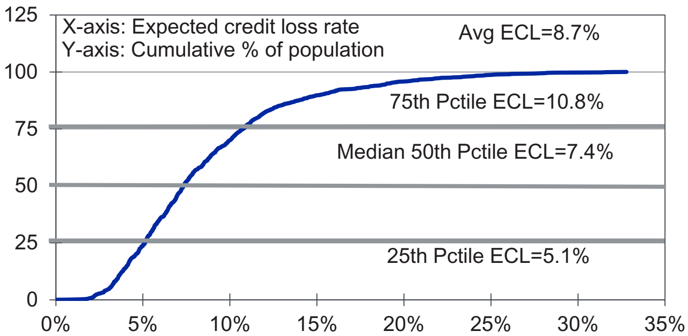
Chart 7: Simulated Unemp. Rates, 25 of 1,000



Sources: BLS, Moody's Analytics

Chart 8: Cumulative ECL Rate

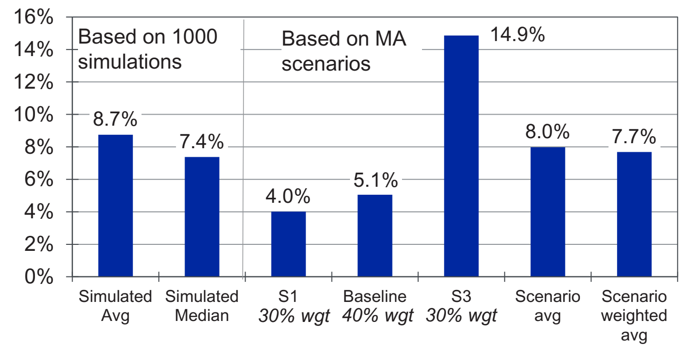
Across simulations



Source: Moody's Analytics

Chart 9: Comparing Lifetime ECL Rates

Expected credit loss rates under different scenarios/simulations



Source: Moody's Analytics

1,000 simulated unemployment rate paths from this exercise.

Chart 8 shows the cumulative expected credit loss rates across all 1,000 paths[4]. Given nonlinearities in the response of losses to economy, we can see how the expected losses computed across all of the simulated paths differ from the baseline scenario.

The other area where this approach scores over the multiple scenario approach is that it recognizes losses far out into the future, beyond the immediate next business cycle. Scenarios that are based on hypothetical assumptions, rather than simulations, attempt to produce a view of the economy only over the near term. Since it is extremely hard to make assumptions about the turning points in the economy beyond the immediate business cycle, the forecasts from these assumption-based scenarios will revert to their long-term trends in the long run[5]. This could result in lower expected credit loss estimates in the far-out future. The simulation approach solves this problem because the forecasts are purely model-driven rather than being dependent on scenario assumptions.

Unfortunately, this very feature—the lack of a narrative underlying the forecasts—makes it hard to interpret the forecasts. This approach is also the most time- and resource-intensive of all the approaches discussed here, severely limiting its adoption to only the largest institutions. Given requirements around forecast disclosures and the myriad of procedures to be implemented prior to the 2020 adoption date, we expect very few—if any—institutions will choose to implement a simulation-based approach to CECL initially. As the process matures and institutions grow confident in their processes, it will be natural for risk managers, auditors and other stakeholders to ask for an increasing number of scenarios to be run. Eventually the process may adopt a full simulation framework.

Chart 9 compares the lifetime expected loss rates estimated from a probability-weighted multiple scenarios approach and the simulated scenario approach using the expected loss rate model described earlier.

Federal Reserve Supervisory Scenarios

Since 2011, the Federal Reserve Board has been publishing a set of hypothetical economic scenarios every year as part of its annual health check of the nation's banking system. These scenarios are used in the Dodd-Frank Act Stress Tests and Capital Planning[6]. While the baseline scenario is similar to the consensus projection from the Blue Chip Economic Indicators survey, the downside scenarios describe an immediate worsening of economic conditions and are designed to assess the strength of the banking industry and its resilience to adverse economic environments. Moody's Analytics does not recommend the use of the supervisory Fed scenarios to estimate CECL for several reasons.

First, the Fed scenario assumptions are limited to a handful of variables (16 U.S. and 12 international). These variables might not represent the risks to an institution's specific investment portfolio. Since the assumptions are at the national level, they also do not recognize the heterogeneity in regional economic performance. To be defendable as CECL scenarios, the Fed scenarios need to be expanded to a larger set of variables and other regions, including subnational. Moody's Analytics does this expansion using a theoretically sound and validated econometric model.

Second, the Fed scenarios go out only 13 quarters. The forecasts would have to be extrapolated over many quarters to be used for estimating lifetime losses and the extrapolation approach will need to be defended with auditors and regulators.

Third, the scenarios are published in the first quarter of every year and are not updated during the rest of the year. This makes the scenarios stale when used for estimating CECL during the latter half of the year since they no longer capture the current risks facing the economy. Although these risks are recognized in a new set of scenarios released in the first quarter of the following year, it also means that the scenarios can change significantly from year to year. For example, in recent years the Fed has experimented

4 We've assigned a floor of 1% to the unemployment rate.

5 The timing and speed of mean reversion depends on the variable in question. In the Moody's Analytics scenarios, for example, U.S. GDP annualized growth rates revert to the historical average of 2% under all the probabilistic scenarios. GDP levels, however, do not converge across the scenarios because of the assumption of hysteresis in output following a shock to the economy.

6 https://www.federalreserve.gov/supervisionreg/files/bcreg20180201a1.pdf

Table 1: Pros and Cons of Different Options

Approach	Pros	Cons	Recommended firm size (by asset size)
Qualitative Overlay	Easiest to explain Easiest to implement	Hardest to defend Hardest to quantify	Smallest
Single Scenario	Easier to implement than multiple scenarios Easy to explain	Likely to produce more volatile expected loss estimates compared with multiple scenarios Requires documentation to support scenario selection	Small/medium
Shadow Scenarios	Less subjective overlays Captures forecast uncertainty compared with single scenario	Involves overlays Does not incorporate multiple scenarios mathematically	Medium
Probability-Weighted Multiple Scenarios	Produces more stable ECL estimates than single scenario	Operationally more complex to implement than single scenario Requires additional documentation to support scenario choice and probability weights	Medium/large
Simulated Scenarios	Produces most accurate ECL estimates Recognize future business cycles	Operationally most complex and time- and resource-intensive Hardest to explain	Largest

Source: Moody's Analytics

with the interest rates assumptions in its adverse scenario—a scenario describing a moderate downturn in the global economy. This means that an institution using the Fed scenarios to estimate CECL every quarter will run the risk of volatile loss reserves at the beginning of every year, while also failing to capture current economic conditions during the rest of the year.

Finally, institutions using the Fed baseline and adverse scenarios to calculate average loss estimates in a probability-weighted approach will invariably end up with conservative estimates unless they also include an upside scenario in the mix to counter the impact of the downside scenario and to provide a more unbiased forward-looking view of the economy.

Summary and recommendations

Although there is no single, ideal CECL solution, institutions should select an approach for leveraging economic scenarios that takes into consideration their overall size and portfolio complexity. Table 1 summarizes the pros and cons of the different options discussed. Qualitative overlays might be sufficient for smaller firms, but they will likely not pass regulatory muster for the large ones. Institutions also need to consider the size and materiality of their individual portfolios. There is no requirement that the same approach be adopted for all portfolios. So a large institution may be able to defend its choice to use qualitative overlays in the forecasting of their smallest nonmaterial portfolios while adopting a more rigorous process for their largest portfolios.

Request More Information on Moody's Analytics Forecasts & Alternative Scenarios for CECL

About the Authors

Sohini Chowdhury is a director at Moody's Analytics. She specializes in macroeconomic modeling and forecasting, scenario design, market risk instruments and CECL solutions. She has overseen many client projects related to stress-testing and other regulatory requirements. She holds a PhD in economics from Purdue University and a master's in applied statistics from West Chester University.

Before joining Moody's Analytics, Sohini taught at the University of Cincinnati.

Cristian deRitis is a senior director at Moody's Analytics, where he leads a team of economic analysts and develops econometric models for a wide variety of clients. His regular analysis and commentary on consumer credit, policy and the broader economy appear on the firm's Economy.com web site and in other publications. He is regularly quoted in publications such as the Wall Street Journal for his views on the economy and consumer credit markets. Currently he is spearheading efforts to develop alternative sources of data to measure economic activity more accurately than traditional sources of data.

Before joining Moody's Analytics, Cristian worked for Fannie Mae and taught at Johns Hopkins University. He received his PhD in economics from Johns Hopkins University and is named on two U.S. patents for credit modeling techniques.

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Moody's Analytics added the economic forecasting firm Economy.com to its portfolio in 2005. This unit is based in West Chester PA, a suburb of Philadelphia, with offices in London, Prague and Sydney. More information is available at www.economy.com.

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