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Economic Scenarios: What's Reasonable and Supportable?

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Introduction

The world is awash in forecasts. Politicians, pundits, analysts and even economists are constantly filling the airwaves with their views on economic issues and how the future is bound to unfold. Forecasts often come with an agenda or other motivation in order to nudge policymakers in a particular direction. But even more neutral analysts can differ in their interpretation of trends, correlations and relationships among economic factors, leading to vastly different forecasts.

Economic Scenarios: What's Reasonable and Supportable?

BY CRISTIAN DERITIS

The world is awash in forecasts. Politicians, pundits, analysts and even economists are constantly filling the airwaves with their views on economic issues and how the future is bound to unfold. Forecasts often come with an agenda or other motivation in order to nudge policymakers in a particular direction. But even more neutral analysts can differ in their interpretation of trends, correlations and relationships among economic factors, leading to vastly different forecasts.

And yet, businesses need to make decisions about how much to produce and where to invest; households need to make consumption and savings decisions; state and local governments need to project tax revenues; utilities need to forecast demand to ensure they have sufficient capacity. Last but not least, banks and lenders need forecasts to ensure they charge a sufficient amount of interest to cover loan defaults and remain solvent during times of stress.

Not only does forecasting make sound business sense, but regulators now require it. U.S. accounting standards are adopting a forward-looking approach that will require lenders to forecast losses over the entire life of the loans on their books. While seemingly innocuous, the Current Expected Credit Loss rule has the potential to increase loss reserves significantly depending on how it is interpreted and implemented. In this article, we explore the forward-looking elements necessary to comply with the CECL guidelines set to go in effect in 2020 for SEC-registered firms and in 2021 for non-SEC registrants. Specifically, we review and make recommendations on the use of economic scenarios in the CECL process along six key dimensions:

- » Financial Accounting Standards Board requirements
- » Forecast methodology
- » Forecast horizon definition
- » Number of scenarios
- » Mean reversion
- » Custom scenarios

We conclude with a discussion of other considerations banks and lenders should bear in mind when developing a forward-looking process in order to comply with the reasonable and supportable requirements of the CECL guidelines.

Requirements for "reasonable and supportable forecasts"

The phrase "reasonable and supportable forecasts" appears more than 30 times in the Financial Accounting Standards Board's CECL standard. Clearly, regulators place great importance on firms supporting the estimates in their financial reports with sound, quantitative data and methods. The use of forward-looking information in loss provision estimates is a new development in the accounting profession, which has traditionally frowned upon the formal incorporation of forward-looking forecasts given the potential for manipulation and bias. Auditors are bound to be particularly cautious as a result, putting the burden on filers to prove that their choices and assumptions do not sway reported results.

In a nutshell, the CECL rule requires lenders to compute an expected lifetime loss projection for each loan (or common cohort of loans) in their portfolios. Companies have wide discretion when it comes to the specific methodology employed to come up with these projections, but at a minimum they are required to consider the historical performance of similar loans, current conditions, and future projections when deriving their estimates. Historical performance data provide the basis for making a projection and are relatively easy to acquire either from lenders' own systems or commercially available databases of industry-level performance such as CreditForecast.com[1]. Current conditions are easily obtainable as well from loan servicing records and economic databases. The biggest challenge for institutions will be the incorporation of unbiased, defensible future projections.

The passage from the CECL guideline that most directly references the use of forecasts reads as follows:

"The measurement of expected credit losses is based on relevant information about past events, including historical experience, current conditions, and ***reasonable and supportable*** *forecasts that affect the collectability of the reported amount. An entity must use judgment in determining the relevant information and estimation methods that are appropriate in its circumstances."*

Amendments allow an entity to ***revert to historical loss information*** *that is reflective of the contractual term (considering the effect of prepayments)* ***for periods that are beyond the time frame for which the entity is able to develop reasonable and supportable forecasts****."*

Source: Page 3, Financial Instruments—Credit Losses (Topic 326), FASB, No. 2016-13, June 2016

Translating this broad guidance into a specific plan of action hinges on answering five key questions, which we address in the sections that follow:

- What is an acceptable methodology for generating forecasts?
- How long is the reasonable and supportable forecast horizon for the forecasts used?
- How should lifetime loss allowance estimates transition or revert to the historical loss experience beyond this forecast horizon?
- Is the calculation of losses under a single economic scenario reasonable and supportable or are multiple scenarios needed? What are the costs and benefits of each approach?
- What are the benefits of using customized versus standard economic forecast scenarios?

Methodology

For an economic forecasting model to be useful for decision-making in general and to meet CECL's "reasonable and supportable" criteria for financial reporting, it should satisfy three criteria:

1. The model should be based on sound, generally accepted economic and statistical theory.
2. The model should incorporate inter-relationships and feedback effects among economic variables such that a shock to one factor (for example, interest rates) impacts all other factors (for example, employment) over time.
3. The model should provide information at varying levels of geographic aggregation in order to capture local economic effects.

The economics profession has yet to coalesce around a preferred forecasting model for predicting the future state of the economy. Techniques range from time series analysis to dynamic stochastic general equilibrium models, machine learning/data mining algorithms, and structural models. As with any model, there are strengths and weaknesses to each methodology.

1 CreditForecast.com is a joint product offering from Equifax and Moody's Analytics that provides volume and performance information for consumer credit products such as mortgage, credit cards and personal loans broken out by geographic, origination vintage, credit score and loan term. More information is available at www.creditforecast.com

Time series models rely heavily on observed trends and are generally most accurate in the very short term. However, this emphasis also makes them highly inaccurate over longer time frames. For example, it is well known that the best forecast of this month's inflation rate is last month's inflation rate, but last month's inflation rate is a poor predictor of inflation one or two years into the future. Particularly damning for use in CECL is their lack of interdependence among factors (such as the impact of interest rate changes on unemployment).

At the opposite extreme, DSGE models emphasize interactions between economic factors through the introduction of complex relationships. But this complexity comes at the cost of intuition and processing speed. Given that CECL calculations need to be made frequently and changes to estimates need to be transparent and communicable to a broad audience, the use of DSGE models may be difficult to maintain in a production environment.

More data-driven or machine-learning approaches have gained favor in other fields, but their use in economic forecasting is limited by the difficulty in interpreting them, their lack of a theoretical foundation, and their susceptibility to extrapolating anomalous or spurious relationships. The lack of transparency and stability of these methods makes these approaches particularly ill-suited for CECL.

Structural macroeconomic models offer a middle ground by taking the approach of estimating a linked system of equations allowing for correlations and feedback effects across economic indicators. Chart 1 provides a schematic view of these connections and how they allow for the propagation of shocks across economics factors. For example, a shock to oil prices in this system will work its way through all of the equations to produce consistent forecasts for all other factors such as wages or house prices. The strength of this approach lies in the simplicity of each individual component. Analysts can interpret the marginal effects of specific driver variables within a given equation in order to understand the relationships embedded throughout the system[2].

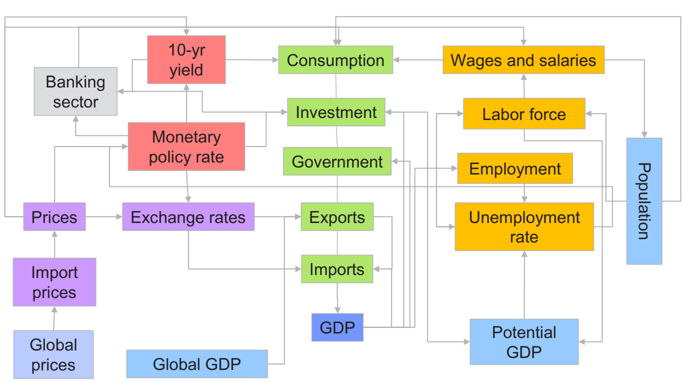
An additional benefit of the structural modeling approach is that it relies on well-established modeling techniques that are used by a wide variety of domestic and international organizations such as the Federal Reserve, the International Monetary Fund, and central banks across the globe. The ability for model users to easily introduce exogenous policy or other shocks on certain variables and forecast the behavior of other factors in a consistent fashion makes them particularly suitable for use in CECL where the economic factors impacting each institution may differ substantially.

Choosing a forecast horizon

In terms of generating economic forecasts, structural models can project the economy 30 years—or even longer. However, they will typically enforce a reversion to long-term trends after a period of two to five years or one "business cycle". Chart 2 provides an example of the GDP growth forecasts from the

2 For additional details on the structural macroeconomic model developed and utilized by Moody's Analytics, see Mark Zandi and Scott Hoyt, "U.S. Macro Model Methodology," Moody's Analytics Special Study, April 2015. www.economy.com/mark-zandi/index

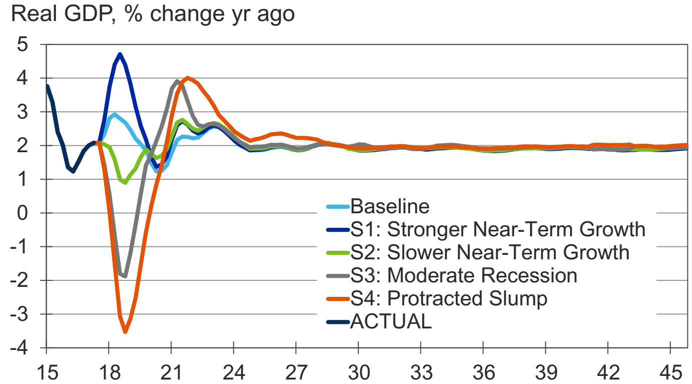
Chart 1: Moody's Analytics Structural Macro Model



Source: Moody's Analytics

Chart 2: GDP Growth Forecast 30 Years Out

Real GDP, % change yr ago



Sources: BEA, Moody's Analytics

Moody's Analytics model. These models do not attempt to capture turning points in the economy—a notoriously difficult exercise given the number of unpredictable external shocks that may hit the economy.

Rather, the forecasts generated are "reasonable and supportable" over a long horizon in the sense that they are estimated based on sound economic theory and decades of observed historical econometric relationships. The speed at which the forecasts revert to long-term average growth rates is based on observed historical patterns of mean reversion that are reflected in model parameter estimates.

Specific recommendations on the forecast horizon to use for CECL will differ across institutions and portfolios. In part the decision will depend on the data and credit loss forecasting models or algorithms employed by each individual institution. For example, a loss forecasting model for residential mortgages built on a short historical performance window may not be reliable over a longer horizon. Institutions will need to weigh the benefits of using a custom model based on their own short history versus a model built on a broader swath of historical industry performance. An industry-level model will be more robust from a forecasting standpoint but may not capture firm-specific nuances from underwriting or servicing practices. A calibrated approach may offer the best of both worlds.

Users of economic forecasts need to recognize the inherent uncertainty around longer-term forecasts. Although a baseline estimate may be unbiased, the confidence interval around it will grow over time given the inherent uncertainty in an economy susceptible to a wide variety of shocks—both internal and external. Turning back to our example of real GDP growth, we can get a sense of the range of possible outcomes around the baseline projection by considering the Moody's Analytics Upside Scenario 1, which represents the 10th percentile in the forecast distribution, and the Moody's Analytics Downside Scenario 3, which represents the 90th percentile. (The baseline is centered at the 50th percentile by construction.)

As shown in Chart 3, the scenarios show significant deviation in the short term, as Scenario 1 represents a stronger near-term expansion while Scenario 3 represents a near-term contraction. After these initial shocks to the economy, the paths converge back to long-run equilibrium growth rates. The implicit assumption is that the scenarios capture one business cycle (either expansionary or contractionary) and the recovery (or return) to long-term trend.

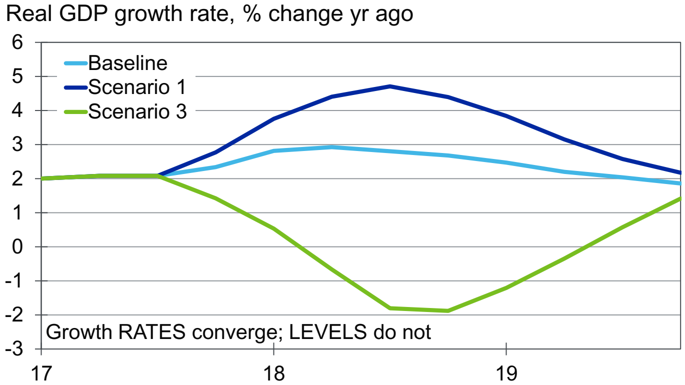
Another example of the widening of intervals can be illustrated with a simple time series model of GDP growth (see Chart 4). Utilizing a simple ARIMA model, we observe that the confidence intervals widen initially before stabilizing.

Bearing model uncertainty in mind, a two- to three-year forecast horizon may be deemed as "reasonable and supportable." Beyond this time frame the confidence intervals in any economic forecasting model will widen considerably. The two- to three-year horizon is also consistent with the guidance offered by most economic prognosticators and regulatory agencies such as the Federal Reserve. The nine-quarter horizon selected for stress-testing by the Federal Reserve further supports the notion that forecasts over this period are reasonable and supportable.

As we will see in future sections, the choice of forecast horizon is linked with the other assumptions and choices that institutions will make in their CECL processes. For example, institutions choosing to

Chart 3: Scenarios Converge

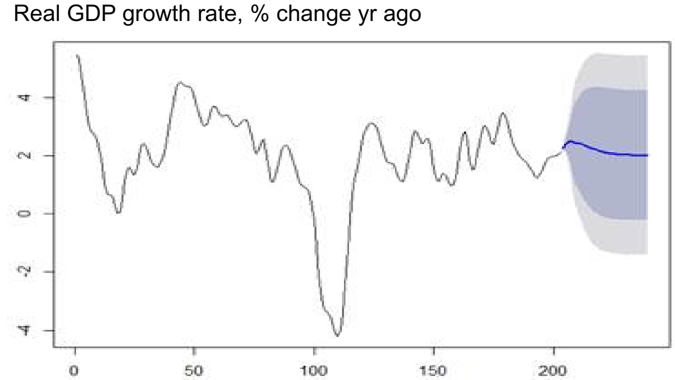
Real GDP growth rate, % change yr ago



Sources: BEA, Moody's Analytics

Chart 4: Confidence Bands Widen

Real GDP growth rate, % change yr ago



Source: Moody's Analytics

project losses across multiple economic scenarios may incorporate the forecast uncertainty that the CECL standard seeks to address more directly, thereby making the choice of the forecast horizon less relevant.

Mean reversion

Closely related to the choice of forecast horizon is the treatment of mean reversion beyond the selected horizon. CECL requires the estimation of losses over the contractual life of loans. The forecast horizon simply determines how much of this estimate will be based on forecast economic conditions versus relying on average historical performance.

Though it may be tempting to rely more on historical loss performance than forecasts under the belief that history is more easily defended than forecasts, this logic may not hold up to regulatory and auditor scrutiny. Determination of historical loss performance has its own set of questions and complexities. For example, what is the relevant historical period? Is all performance observed historically? What if there were significant changes to underwriting or servicing that make a portion of history less relevant for the current portfolio? Should historical average performance be calculated only over the last few years as a result? Does failing to include the Great Recession bias results downward? Does choosing to include the recession bias results upward?

Auditors will want assurances that the selected historical performance is just as "reasonable and supportable" as the forecasts that filers will generate. As the old saying goes, there is no free lunch.

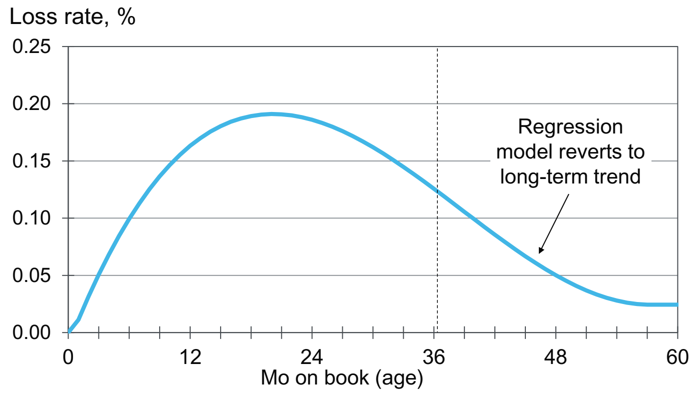
Having determined an appropriate forecast horizon and defined historical loss rates to use, there are three options when it comes to implementing mean reversion in CECL estimates:

Option 0: Do not revert to historical credit loss rates if the loss forecasting model already has reversion built into it.
Option 1: Revert to historical loss rates **immediately** after the determined forecast horizon.
Option 2: Revert to historical loss rates **gradually** after the determined forecast horizon.

The impact of these choices can be illustrated with a set of charts. For the sake of simplicity, we focus on a single cohort of loans originated at the same time with similar risk characteristics. However, the analysis is generalizable across a portfolio of loans with mixed seasoning and credit quality.

From the standpoint of forecasting consistency, Option 0 is the preferred approach. Ideally, a properly specified credit loss model would address the issue of mean reversion internally in a quantitatively consistent fashion. For example, suppose that only three years of historical data are available for a loan portfolio with a contractual life of five years. Further, assume that the vast majority of these 60-month loans are paid off in full by month 24. A discrete time hazard model with competing risks would properly capture this behavior such that only a few loans are forecast to survive to month 36. Although the model has not been estimated on any loans that survived for more than three years, the model could be specified in such a way that the extrapolated forecasts up to month 60 are still reasonable (see Chart 5). This approach

Chart 5: Mean Reversion Option 0



Sources: BEA, Moody's Analytics

would be preferable to simply ignoring behavior beyond 36 months or assuming forecast performance jumps up to the historical portfolio average—without controlling for the age of the loans or other loan characteristics. A well-formulated econometric model will already control for all of these factors in generating a longer-term forecast.

While an internally consistent credit model is ideal because it requires no external overlays or assumptions, there are situations in which the use of such models is neither feasible nor practical. Under Option 1, suppose we have a 36-month baseline forecast for the conditional loss rate that we feel comfortable defending to the "reasonable and supportable" standard. We also have historical data on the average conditional default rate by loan age for loans with similar risk characteristics such as a loan-to-value ratio or credit score in the case of a consumer credit portfolio. As illustrated in Chart 6, we could simply splice these two series together in order to generate a lifetime forecast for all of the loans in the cohort.

Obviously the main issue with this approach is that it may introduce an inconsistent and undesirable jump-discontinuity in the forecast. If the jump is relatively small, then it may not materially impact the lifetime loss projection in the grand scheme of things even though it may be aesthetically displeasing.

Alternatively, we may choose to smooth out the jump through the use of a transition function in Option 2. For example, we could define our projection as the weighted average of the baseline forecast and the historical data where the weights on the forecast values decline over a six-month period while the weights on the historical series increase (see Chart 7).

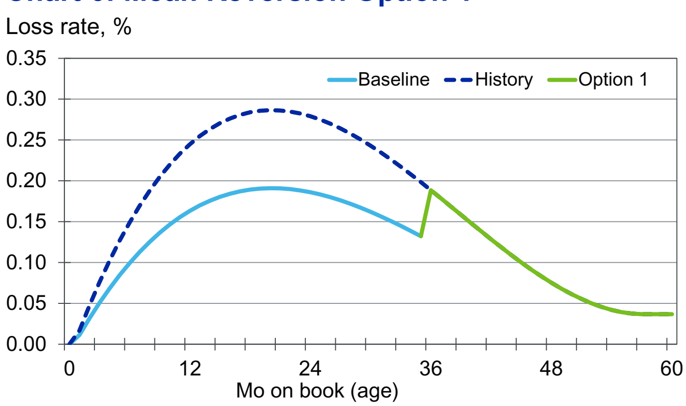
We reiterate that the selected mean reversion process relies on a number of assumptions that could critically impact the resulting loss estimates including, but not limited to, the need to collect representative historical data and extrapolate historical performance beyond the observable historical period. This may be particularly problematic for a lender with a relatively young portfolio and limited performance history. For these reasons, we believe that a properly specified, econometric loss forecasting model that takes these factors into account internally may provide a more accurate and more easily defendable solution for mid- to large-size institutions.

How many scenarios are sufficient?

Institutions will also need to consider the number of scenarios they should use to generate their forecast estimates. The use of a single scenario is straightforward and reduces the burden of having to defend multiple scenarios—though it increases the scrutiny on the selected scenario. However, the cost of developing, maintaining and defending multiple scenarios may pay off in the form of less volatile reserves and earnings. The use of multiple scenarios may also mitigate or eliminate the sensitivity of loss estimates to the choices surrounding forecast horizon and mean reversion.

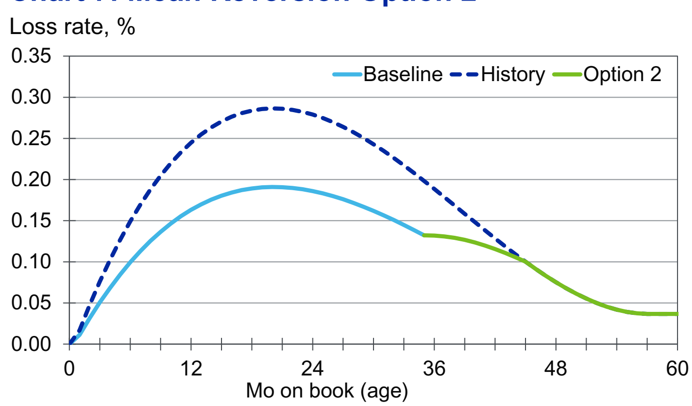
Going into effect in January, International Financial Reporting Standard No. 9, or IFRS 9, instructs institutions outside of the U.S. to run their credit loss forecasts using "probability weighted scenarios." While the specific number and types of scenarios are still left to each institution's individual discretion, most firms are opting to run their analyses under three scenarios: one upside, one downside, and one baseline

Chart 6: Mean Reversion Option 1



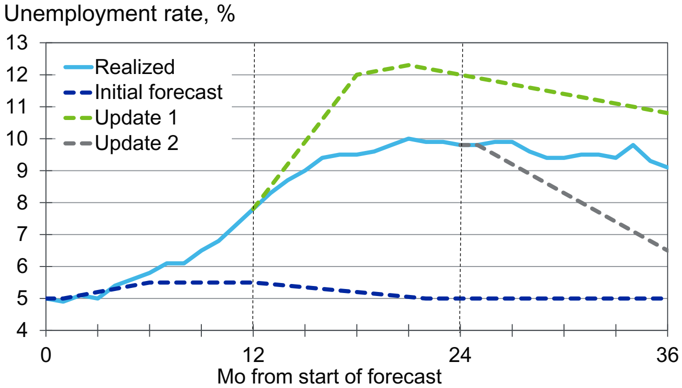
Sources: BEA, Moody's Analytics

Chart 7: Mean Reversion Option 2



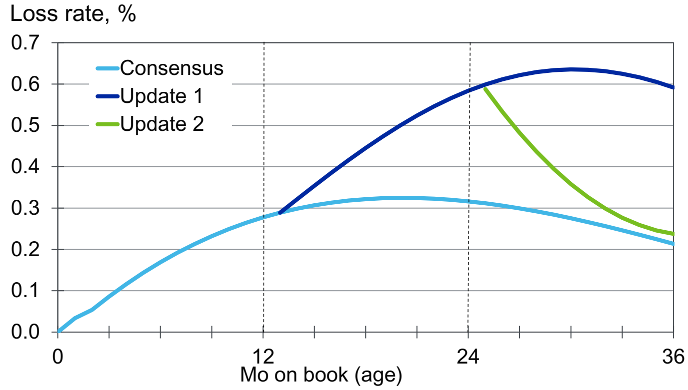
Sources: BEA, Moody's Analytics

Chart 8: Consensus Unemployment Forecasts



Sources: BLS, Moody's Analytics

Chart 9: Loss Forecasts With Consensus



Sources: BEA, Moody's Analytics

view. The need to attach probability weights to each scenario requires the use of well-grounded, statistically driven quantitative methodology such as one of the ones discussed previously. Individual model users may still overlay qualitative adjustments to account for idiosyncratic circumstances, but these should be relatively minor and well-documented.

Although CECL does not ***require*** the use of multiple scenarios, the guidelines do not ***forbid*** the practice. Many institutions—especially larger banks and multinational firms reporting financials in multiple jurisdictions—will likely adopt the multiple scenario approach for consistency with both international standards and standard risk management practices.

An additional benefit from running multiple scenarios is that computed loss provisions may be less volatile over time. To appreciate this, it is instructive to walk through an example.

Suppose the unemployment rate is a key economic driver of losses in a portfolio of loans we are modeling. In the case where we use a single forecast, we may look to a consensus forecast, which combines the forecasts of a variety of professional forecasters for a forward-looking view. Given a strong emphasis on the short term, professional forecasters may tend to extrapolate current conditions forward rather than make bold predictions in one direction or the other. As a result, the initial forecast in our example is relatively flat—projecting the current level of unemployment forward (see Chart 8).

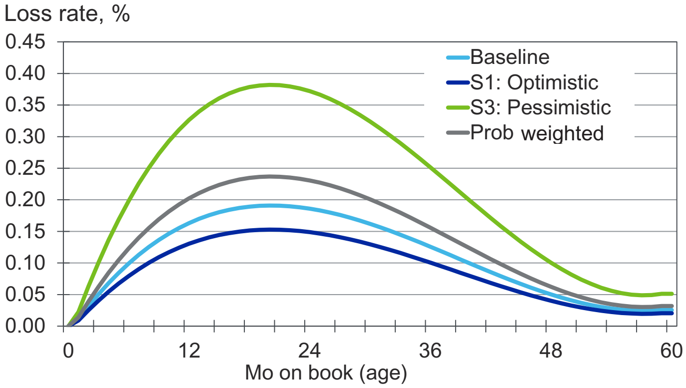
Suppose that the economy deteriorates in the subsequent 12 months with the unemployment rate rising from 5% to 8%. At this point, a consensus poll is taken again. Having been proven wrong in the preceding months, professional forecasters may aggressively update their projections calling for a 12% unemployment rate in the subsequent 12 months (see the "Update 1" series in Chart 8).

Next, suppose the economy does indeed deteriorate from months 13 to 24, but does not perform as poorly as anticipated, with unemployment peaking at 10%. The professional forecasters again take this updated information into account and expect improvement with the unemployment rate falling to 7% in the next 12 months (see the "Update 2" series in Chart 8). As demonstrated by the "Realized" series, the view proves overly optimistic, as the unemployment rate drops only to 9%.

The impact of these updates on a firm's loss allowance is illustrated in Chart 9. The initial loss allowance would have had to have been increased significantly at the first update to account for the forecast error during the first 12 months and the large upward revision in unemployment projected for month 13 to 36. The loss allowance would then have had to have been revised downward at month 24 because of the view that the economy would improve over the subsequent 12 months. But the allowance would have had to have been raised back up again at month 36 to account for the forecasters' overly optimistic view on the recovery.

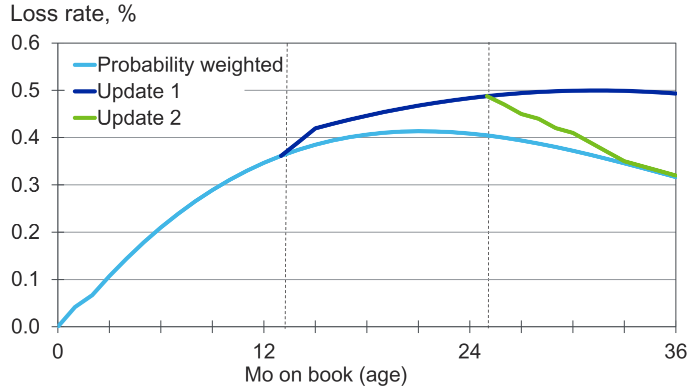
In contrast, a probability weighted approach would consider both upside and downside scenarios in addition to a baseline when developing a forecast. For example, the initial forecast would be the weighted average of the baseline, Scenario 1 and Scenario 3 forecast illustrated in Chart 10.

Chart 10: Probability Weighting Loss Forecasts



Sources: BEA, Moody's Analytics

Chart 11: Loss Forecasts With Prob Weighting

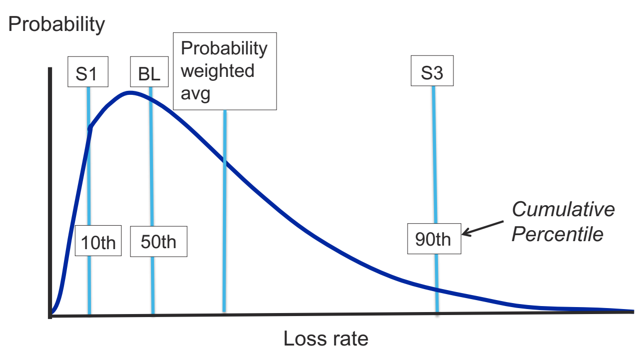


Sources: BEA, Moody's Analytics

By accounting for losses across a variety of scenarios, the initial loss reserve projection will be higher than the single-scenario approach, but it will require less adjustment, as shown in Chart 11.

By their nature, the distribution of loan losses tends to be highly asymmetric, as borrower responses to economic shocks are nonlinear. The distribution of credit losses tends to be fat-tailed, as illustrated in Chart 12. Losses may not change materially between a "great" versus an "average" economy, but they may increase exponentially in a "bad" economy.

Chart 12: Loss Distributions Are Skewed



Source: Moody's Analytics

As a result, firms that project losses using a single scenario could experience significant changes to their forecasts as the scenario is updated. Averaging the loss forecasts across multiple scenarios smooths out some of this volatility, making the forecasts less beholden to short-term views.

Smaller institutions may choose to run their forecasts using only one scenario given costs and other considerations, but they should be aware of the volatility risk involved. They should engage in periodic sensitivity analysis to assess the potential impact to their loss provision estimates if the economy turns out to perform much worse than projected under their selected scenario. Qualitative adjustments—with supporting evidence—may be appropriate for firms opting to use a single-scenario approach.

Moody's Analytics Approach to Probability Weighted Scenarios

To assist firms with their forecasting exercises, Moody's Analytics produces a range of alternative economic scenario forecasts every month[3]. Thousands of simulations are run to generate a distribution of possible economic outcomes from which Moody's computes the probabilities for five standard scenarios, namely:

BL	Baseline	50th percentile
S1	Scenario 1: Stronger Near-Term Growth	10th percentile
S2	Scenario 2: Slower Near-Term Growth	75th percentile
S3	Scenario 3: Moderate Recession	90th percentile
S4	Scenario 4: Protracted Slump	96th percentile

From this menu of alternative scenarios, institutions can create a probability weighted CECL projection most easily by running their loss models for the baseline scenario, Scenario 1 and Scenario 3. Weights for the individual scenarios are defined based on the intermediate point between two adjacent scenarios as follows:

Probability of S1 = S1 percentile + (Distance Between Baseline and S1 Percentiles) / 2
= 10% + (50% - 10%) / 2
= 30%

Probability of S3 = S1 percentile + (Distance Between Baseline and S3 Percentiles) / 2
= 10% + (90% - 50%) / 2
= 30%

The baseline gets the residual probability of 40% ensuring that the discrete probabilities add to 100%. This approach uses the statistical properties of the forecast distribution to compute weights, which is defensible in that it is quantitatively driven. However, each institution should evaluate its own exposures and position on the future economy and adjust weights accordingly. For example, a bank operating primarily in an economically depressed industry may choose to overweight Scenario 3 and underweight Scenario 1.

3 For additional details on the construction of Moody's Analytics alternative scenarios, see Sohini Chowdhury, "Calibrating U.S. Macroeconomic Alternative Scenarios," Regional Financial Review, Moody's Analytics, January 2015.

Custom scenarios

The use of readily available standard scenarios provides an easy solution for addressing the forward-looking requirements of CECL. Auditors and regulators are more likely to be familiar with commercially available forecasts, thereby lessening the burden of proof that individual institutions will need to provide if they develop their own scenarios. The use of standard scenarios is particularly attractive for smaller institutions, which may lack both the historical data and expertise to develop their own fully fledged economic models and scenarios. After all, banks are in the lending business, not the economic scenario-generation business.

Larger institutions will likely opt to use scenarios that have been tailor-made or customized to their unique geographic and business footprint. For example, a bank with disproportionate exposure to the auto manufacturing and lending industries in the Midwest may choose to develop a set of scenarios that emphasizes the risks due to gasoline prices and unemployment in the metropolitan areas in which it operates. By customizing scenarios, institutions may be able to better capture and disclose the risks to their portfolios. More accurate and targeted scenarios may also reduce the need for qualitative adjustments or "uncertainty buffers," thereby reducing loss allowance estimates.

Considerations and recommendations

Regardless of the specific choices made around the use of forward-looking information in their loss forecasts for CECL, all institutions will be expected to demonstrate that their forecasts are realistic and unbiased. The economic forecasts utilized will need to be constantly back-tested and refined to capture changes in underlying economic indicators and new economic relationships. Scenarios will need to be updated at least quarterly to reflect recent data and policy changes so as to impact the forecasts in a timely fashion.

While we have focused on the economic forecasts that will drive loss estimates for CECL, the importance of ensuring that asset-specific, credit loss forecasting models are both reasonable and supportable cannot be understated. Firms will want to ensure that the underlying credit models they use are based on sufficient performance history to generate robust, meaningful loss estimates that are sensitive to changing economic conditions. They will want to confirm that the observed history used to develop their credit loss models is relevant for the time horizon projected. For example, it may be unreasonable to assume that we may accurately forecast losses over a 10-year horizon with forecast stress based on just two years of historical data collected in a benign economic environment.

In summary, we recommend:

1. For the largest institutions, the use of multiple custom economic scenarios provides a wide range of estimates that may be weighted to derive the loss allowance calculation for CECL. Credit loss models should forecast losses over the contractual or behavioral life of loans in the portfolio, making estimates less sensitive to explicit decisions around the reasonable forecast period and mean reversion method.
2. For midsize institutions, standardized economic forecasts provide a reasonable solution. Running loss forecasts along multiple scenarios and then weighting them provides the most quantitative, defensible approach while reducing the potential for volatility in quarter-to-quarter updates.
3. For institutions with small portfolios or that lack the capability to run multiple loss forecasts efficiently, a single scenario approach is reasonable. In this case, our recommendation is to set the "reasonable and supportable" forecast horizon at either two or three years with gradual reversion to average historical losses over a period of six months.

For all these recommendations, special attention needs to be paid to the credit loss forecasting models that will utilize economic forecasts as inputs. Users need to understand the forecast uncertainty and determine a reasonable and supportable forecast horizon for these models in conjunction with the choices around the economic forecast inputs.

Institutions and auditors are rightly concerned about the implementation of CECL and the implications it could have on financial statements, profitability and capitalization levels. While there are challenges, there are also opportunities to better align lenders' origination and pricing functions with their financial accounting so that there is one consistent view of risk throughout the life cycle of lending. Provided that forecasts are used as tools rather than crystal balls, they can provide users with the information needed to manage risk in more quantitative, econometrically driven fashion. Over time, these tools will allow lenders to make more informed decisions along with complying with CECL for financial reporting.

Background: Moody's Analytics Economic Scenarios

The economic forecasts available from Moody's Analytics are well-grounded in decades of economic theory and supported by robust quality-control processes to ensure all input data are up-to-date and accurate. But what makes them "reasonable and supportable"?

The quality of the Moody's Analytics forecasts benefits from the long history of running a monthly forecasting process as well as their large user base. The forecasts have been produced for more than 25 years by a team of economists, database managers and operational engineers to ensure quality and accuracy. In addition, widespread adoption of the forecasts by hundreds of banks, credit unions, utilities, government agencies, and real estate developers has created a collaborative community of model users whose input is extremely valuable in ensuring and enhancing the quality of the forecasts. Annual forecast quality reviews along with forecast tracking and model validation reports are available to allow users to understand the quality of the forecast outputs relative to the volatility of historical economic indicators. Extensive model documentation discloses the specification and parameter estimates of all of the variables in the Moody's Analytics economic model providing users with full transparency and insight into the forecasting process. For more information, visit https://www.economy.com/products/alternative-scenarios

About the Author

Cristian deRitis is a senior director at Moody's Analytics, where he develops econometric credit models for a variety of asset classes. His regular analysis and commentary on credit, housing, mortgage markets, financial regulatory reform, 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 and New York Times for his views on the economy and consumer credit markets.

Before joining the Moody's Analytics West Chester PA operation, 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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Concise and timely economic research by Moody's Analytics supports firms and policymakers in strategic planning, product and sales forecasting, credit risk and sensitivity management, and investment research. Our economic research publications provide in-depth analysis of the global economy, including the U.S. and all of its state and metropolitan areas, all European countries and their subnational areas, Asia, and the Americas. We track and forecast economic growth and cover specialized topics such as labor markets, housing, consumer spending and credit, output and income, mortgage activity, demographics, central bank behavior, and prices. We also provide real-time monitoring of macroeconomic indicators and analysis on timely topics such as monetary policy and sovereign risk. Our clients include multinational corporations, governments at all levels, central banks, financial regulators, retailers, mutual funds, financial institutions, utilities, residential and commercial real estate firms, insurance companies, and professional investors.

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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