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Gauging CECL Cyclicality

Introduction

The Federal Reserve and other banking regulators have worked diligently since the financial crisis to reform the financial system and put it on much sounder financial ground. They have required financial institutions to increase their capital and liquidity, improve their risk management functions and oversight, and have taken macroprudential steps to cool overheated lending activity.

The next big reform is a sea change in the way financial institutions account for their loan losses. Under existing incurred loss accounting rules, loan losses are not recognized in financial statements until it is probable (based on available information) that a loan is impaired and the amount of loss can be reasonably estimated. A loan's delinquency status is one example of a factor impacting the probability that a loss has been incurred. The new accounting standard, known as Current Expected Credit Loss, or CECL, requires banks to add to reserves when loans are originated, based on historical information, current conditions, and "reasonable and supportable" forecasts.

The American Bankers Association has called CECL the "most sweeping change to bank accounting ever." That is not hyperbole. This arcane change to the accounting rules has big implications for the way institutions operate and the amount of credit they provide. Since the availability and cost of credit are critical to the economy's performance, CECL will likely also have a meaningful impact on the business cycle.

Because Securities and Exchange Commission registrants must adopt CECL by 2020, it is garnering significant attention. Bankers are just now grappling with how to implement the standard and what it means for their loan losses, profitability and lending. Many in the banking community worry that CECL will fail to achieve its principal intended purpose of reducing the procyclicality of the existing incurred loss accounting standard.

This paper should allay these concerns. We provide empirical support for the conclusion that the CECL standard will be less procyclical than the incurred loss standard. CECL will achieve its goal of encouraging lenders to reserve for eventual losses earlier in the lifecycle of their loans than they do today. As a result, CECL will result in easier underwriting and more lending in recessions, and tighter underwriting and less lending in boom times, than under the incurred loss accounting standard. CECL will lower the odds that the financial system and economy will suffer a fate similar to the financial crisis and economic downturn suffered a decade ago.

Gauging CECL Cyclicality

BY CRISTIAN DERITIS AND MARK ZANDI

The Federal Reserve and other banking regulators have worked diligently since the financial crisis to reform the financial system and put it on much sounder financial ground. They have required financial institutions to increase their capital and liquidity, improve their risk management functions and oversight, and have taken macroprudential steps to cool overheated lending activity.

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This paper should allay these concerns.[1] We provide empirical support for the conclusion that the CECL standard will be less procyclical than the incurred loss standard. Our analysis is based on the Freddie Mac portfolio of single-family residential mortgage loans. The results depend on modeling choices and assumptions, but based on our knowledge of how lenders will implement CECL, we find that the new accounting standard will result in substantially less procyclicality in loss reserving. That is, during the housing boom in the mid-2000s, CECL would have boosted reserves compared with the incurred loss standard, and in the subsequent housing bust, reserves would have been lower (see Chart 1).[2]

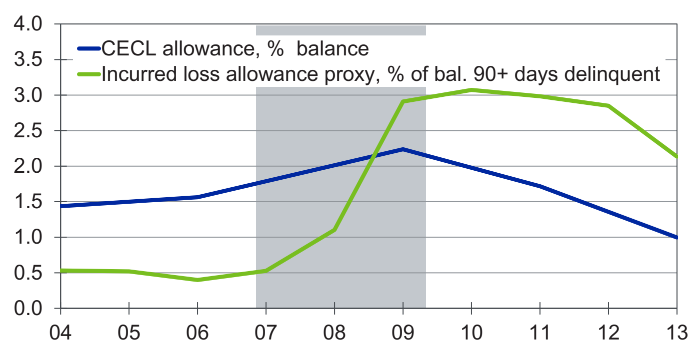
CECL would not have been countercyclical, because the unanticipated deterioration in the economy during the Great Recession would have caused CECL loss reserves to increase, but the increase would have been much smaller than the incurred loss allowance. And this analysis likely understates the benefit of CECL, as it does not consider likely changes in lenders' responses to the new standard. Faced with an increasing loss allowance on loan originations in the housing boom, lenders would have been strongly incented to curb their subprime lending at that time, likely making CECL even less procyclical.

CECL will achieve its goal of encouraging lenders to reserve for eventual losses earlier in the lifecycle of their loans than they do today. As a result, CECL will result in easier underwriting and more lending in recessions, and tighter underwriting and less lending in boom times than under the incurred loss accounting standard. CECL will be less procyclical than the existing incurred loss standard. Therefore, CECL will lower the odds that the financial system and economy will suffer a fate similar to the financial crisis and economic downturn suffered a decade ago.

Chart 1

CECL Is Less Procyclical

Credit loss rate, % balance

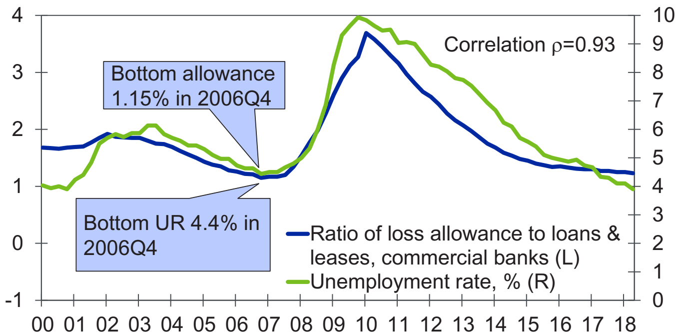


Source: Moody's Analytics

Chart 2

Incurred Loss Method Highly Procyclical

Comparison of loss allowance ratio to unemployment rate

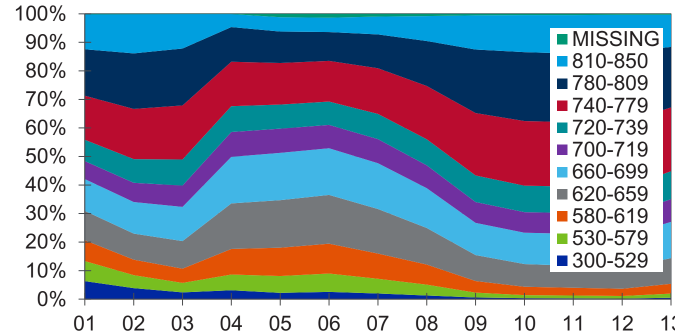


Sources: FDIC, BLS, Moody's Analytics

Chart 3

Lending Quality Loosened During Boom

Mortgage loan volume by borrower's credit score, % orig. volume



Sources: CreditForecast.com, Moody's Analytics

Incurred loss procyclicality

There is little debate that the existing incurred loss accounting standard is highly procyclical. That is clearly evident in the housing boom and bust of a decade ago. During the boom when unemployment was at its nadir and house prices at their peak, loss reserves were low and falling. Conversely, during the housing bust when unemployment soared and house prices collapsed, reserves surged (see Chart 2). Reserves peaked in the first quarter of 2010, soon after unemployment topped out at 10% and just prior to when house prices hit their nadir.

The high correlation between the unemployment rate and loss reserves was the key motivation for the Financial Accounting Standards Board to develop CECL. During the crisis, investors complained that financial statements did not reflect the inherent risk of losses in loan portfolios despite the fact that credit spreads were widening at an alarming rate. Auditors were uncomfortable with lenders rapidly revising their loss reserves every quarter throughout the crisis. A 2009 speech by then U.S. Comptroller of the Currency John Dugan laid out the dissatisfaction with the incurred loss model from the regulators' perspective and advocated for a less procyclical system. Even the banks were dissatisfied with the incurred loss system. Despite having discretion to increase their loss reserves based on nonquantitative factors, the subjective nature of these adjustments exposed them to difficult questions from their auditors and investors.

Economists are also no fans of the procyclicality of incurred loss accounting, because it exacerbates the credit and business cycles. Historically, we observe periods when loan defaults are low, lending standards are loose, and credit is amply available, followed by times of higher defaults, tighter lending standards, and reduced credit availability (see Chart 3). Generally, this credit cycle is closely related to the business cycle, as easy credit turns economic good times into unsustainable booms, and tight credit exacerbates the economic tough times.[3]

There is thus a clear rationale to end incurred loss accounting. The question is whether CECL will be meaningfully less procyclical. It will be if it incents financial institutions to reserve more in the boom times when underwriting standards are low and credit overflowing, and to reserve less in the tough times when standards are high and credit is constrained. Our analysis shows that it does.

Other views

There are vocal critics of CECL in the banking community, including the American Bankers Association and the Bank Policy Institute, a trade organization for generally larger banks.[4] Chief among critics' concerns is that CECL will not be less procyclical than the existing incurred loss system.

However, the critics' analysis is severely limited. It is based on Federal Deposit Insurance Corp. bank call report data for loss reserves and charge-offs available at a portfolio level. The FDIC data are insufficient for an analysis of CECL in two important ways. First, call reports do not provide information on either the lending profile or the seasoning of the underlying loan portfolio. We do not know if observed losses are high because a bank has engaged in lending to lower-quality borrowers or because the economy has deteriorated.

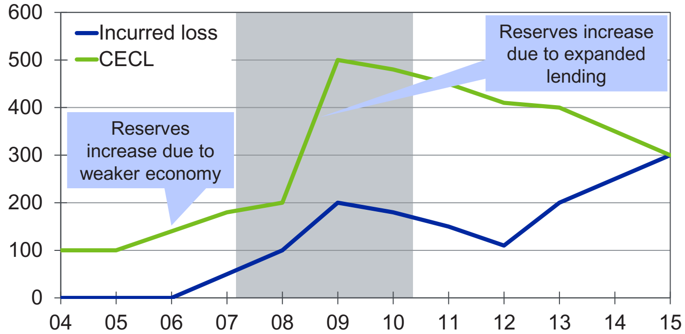
An understanding of seasoning or aging is also crucial for analyzing CECL. We do not know if the losses reported in call reports are associated with young loans, older loans, or something in between. Under CECL, banks will be required to update the loss estimates for each of the loans in their portfolios on a quarterly basis starting from origination. They will know the age of all loans on their books and will adjust their forecasts given the knowledge that the likelihood of default typically goes down as loans age. Not explicitly accounting for loan quality, seasoning and the economy is a significant shortcoming, given the differences between lending portfolios today and a decade ago.

Another serious limitation of the FDIC bank call report data is that the information was collected under the incurred loss accounting regime. The data thus encapsulate the accounting rules and behavioral responses that were in place at the time. Correlating economic data with this history can shed light on how procyclical the existing accounting standard has been. It clearly has been highly procyclical—hence, the motivation for change. However, the aggregate

Chart 4

Behind the Increase in Reserves

Hypothetical credit losses for Prudent Credit Union, $ ths



Source: Moody's Analytics

historical data cannot provide insight into how the new CECL accounting would have changed reserve estimates in the past. To borrow an analogy, unless we know all the ingredients, it is impossible for us to understand how a new recipe will change the taste of a cake.

To account for these limitations, our analysis of CECL's impact on loss reserves utilizes a detailed, publicly available loan-level dataset of single-family residential mortgages guaranteed by Freddie Mac. To be sure, it is just one of the asset classes that lenders will need to model under CECL, and results will vary across assets. But given the outsize role that residential mortgages played in the Great Recession, it is particularly relevant for our understanding of CECL.

Explaining loan loss cyclicality

The cyclicality of loan losses and by extension loan loss reserves is driven by three key factors: the credit quality of originated loans, origination loan volume, and the economy's performance. While CECL estimates will be impacted by forward-looking economic assumptions, it is a mistake to ignore the impact that credit quality and origination volume will have on individual banks' loss estimates. If CECL effectively increases the cost of riskier loan originations during boom times, lenders will respond by tightening standards or increasing interest rates for these loans.

To illustrate the impact of these factors, consider the hypothetical case of Prudent Credit Union. PCU has historically had a very strong credit culture, maintaining the same lending standards in good and bad economic times. It only provides mortgages to borrowers with high credit scores and with down payments of more than 25%. PCU lost market share to aggressive subprime lenders during the housing boom because of their resolute standards—at the height of the bubble in 2006 the lender booked only $10 million in loans. However, in the wake of the housing market collapse and the failure of its aggressive competitors, its loan volume expanded quickly, tripling to $30 million at the height of the Great Recession in 2009.

Not unexpectedly, PCU experienced a sharp increase in delinquency on its 2006 originations when the recession began in 2008. By 2010, losses on these loans rose to 2%. In contrast, the 2009 book would go on to experience a 1% loss rate, which is close to the historical norm.

Chart 4 illustrates what PCU's loss reserves would have been under incurred loss accounting and CECL. At first blush one might conclude that the loss reserves are more procyclical under CECL, but our analysis needs to account for origination effects. Reserves rose in 2009 not because of the lender's failure to predict a recession, but because of expanded lending. The increased credit availability during the downturn is precisely the outcome that regulators would hope for to counteract the contractionary forces in the economy.

The overall loss reserve in 2009 would have been higher under CECL, but PCU's experience is precisely what we would hope for. For one, reserving on the 2006 book occurred earlier than under the incurred loss model with a smaller jump in reserves in 2008. Second, the higher initial CECL reserves prevented PCU from bowing to market competition and expanding lending earlier. By preserving its capital, it was able to expand its lending in 2009 when the rest of the market pulled back.

A portfolio-level analysis would be unable to capture these effects. Without more granular data, we would be unable to attribute changes in loss reserves to changes in origination quality, origination volume or economic forecasts. Without controlling for these factors, Prudent Credit Union's behavior could be considered procyclical, when it was anything but.

Mortgages under CECL

To empirically test how CECL will work, we modeled and projected expected lifetime losses for Freddie Mac's guaranteed mortgages as of December 2004, 2006, 2009, 2011 and 2013. By so doing, we are able to determine what would have happened to reserves if CECL had been in place before, during and after the financial crisis and Great Recession.

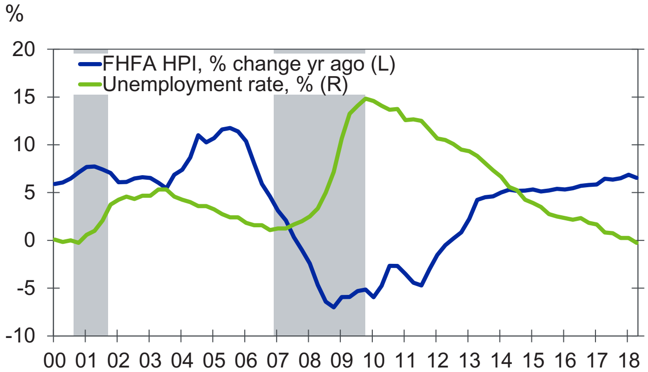
Any assessment of expected credit losses requires two components: (1) a model of credit loss performance that is sensitive to economic conditions; and (2) a set of economic forecasts to use in this model.

The CECL guidelines do not dictate a methodology for estimating credit losses, leaving it to each institution to determine what is appropriate given the size and complexity of its loan portfolio. Larger institutions will opt to use more robust statistical and econometric models in order to properly incorporate correlations and sensitivities to economic factors. Smaller institutions may choose to account for these sensitivities through more qualitative judgments given resource constraints and the materiality of their portfolios. However, even the smallest institutions must estimate CECL reserves at loan origination, suggesting they will adjust their forecasts based on the credit characteristics of newly originated loans.

We use a vintage-cohort based approach for our assessment of Freddie Mac's loans. This method allows us to capture key differences in origination volume, credit quality and performance by origination month while minimizing the complexity and computa-

Chart 5

Before, During, After the Great Recession



Sources: FHFA, BLS, Moody's Analytics

tional requirements of a loan-level model. That said, a loan-level approach for CECL is certainly possible and a methodology we regularly employ.

Freddie Mac provides origination data on mortgages beginning in 1999, including borrowers' credit scores and loan-to-value ratios among other credit characteristics. The current payment status for each loan is also provided on a monthly basis from the time of origination onward. The entire database consists of about 24 million loans that translate into 1.13 billion loan-month observations.

We combined these loan-level data into cohorts defined by credit score, LTV and origination month. We followed typical industry practices for defining the ranges of credit score and LTV ratio in each of our cohorts.[5] For the combination of each of these three factors, we computed the number of loans that were outstanding or delinquent as well as the number of loans that either defaulted or paid off in each subsequent month after origination.

To this vintage-cohort level dataset, we added three key economic factors by reporting month: the unemployment rate, the Federal Housing Finance Agency house price index, and the interest rate on the 10-year Treasury bond. We computed several transformations for each of these variables including the 12-month difference in the unemployment rate and the 10-year Treasury rate as well as the year-over-year percentage difference in the FHFA house price index. We also computed changes in these variables from their origination values. This final set of variables proved to be particularly predictive in modeling default and prepayment performance, because borrowers typically choose to default on their loans based on the amount of equity they have in their property. A drop in interest rates relative to loan origination is a significant predictor of whether a borrower will refinance an existing mortgage.

We used a fractional logit model specification to estimate each of the default and prepayment outcome variables. We utilized a variety of categorical variable interactions and piecewise linear splines in order to capture nonlinearities in the response of borrower default and prepayment to credit quality, seasoning (that is, age) and economic variables.

For the most part, the model fit the cohort-level data well with significant performance differences across each of the credit score and LTV categories (see Table 1). Sensitivity to economic indicators was both significant and sensible. With this model, which is relatively easy to operate, we are ready to create the forward-looking economic scenarios.

Retrospective economic scenarios

To assess how loan loss estimates would have changed before, during and after the Great Recession, we need to generate economic forecasts for the key drivers in our credit models, including the FHFA house price index, the unemployment rate, and the 10-year Treasury yield. Although Moody's Analytics has been producing economic forecasts for nearly 30 years, it did not start producing alternative economic scenarios until 2010. Moreover, the Moody's macroeconomic model has been overhauled significantly since the financial crisis to more formally integrate the banking and financial sectors into the model. The Moody's model is a fully endogenous global economic model that links the economies of 73 countries via trade flows, foreign investment, currency movements, and equity and bond markets. The model allows users to determine the impact of a range of shocks, including to trade, monetary and fiscal policies, asset prices, and oil and other commodity prices.

Using the current version of the Moody's global macroeconomic model, we generated baseline and alternative scenarios for five start dates, including December 2004, December 2006, December 2009, December 2011 and December 2013. These start dates were selected in order to reflect forecasts that would have been made prior to, during and after the onset of the Great Recession, and to also capture differences in the cycles for unemployment, house prices and interest rates (see Chart 5).

Documentation describing the Moody's global macroeconomic model and the methodology used to produce forecasts are available.[6] For the purposes of this analysis, we produced a baseline scenario that is centered at the midpoint of potential economic outcomes by construction. The baseline is consistent with a 50% probability that the economy would perform like this scenario or better/worse. We also produced four alternative scenarios, two upside and two downside, consistent with the baseline at each forecast start date. In constructing these scenarios, we utilized all historical economic data up to the forecast start date. More specifically, the alternative scenarios are:

- Scenario 0 - A very strong upside scenario consistent with a 4% probability that the economy would perform like this scenario or better;
- Scenario 1 - A strong upside scenario consistent with a 10% probability that the economy would perform like this scenario or better;
- Scenario 3 - A strong downside scenario consistent with a 10% probability that the economy would perform like this scenario or worse; and
- Scenario 4 - A very strong downside scenario consistent with a 4% probability that the economy would perform like this scenario or worse.

Table 1: Mortgage Prepayment and Default Model

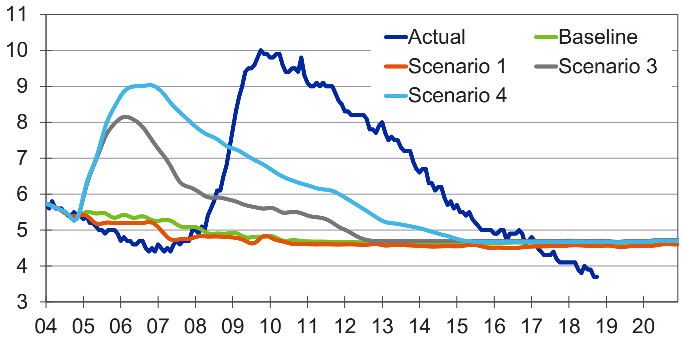
Explanatory variable	Category definition	Prepayment Coef.	Prepayment StdErr	Default Coef.	Default StdErr
Age (piecewise linear)	(0-6)	0.2275	0.0057	0.1893	0.0992
	(6-12)	0.0729	0.0032	0.0573	0.0525
	(12-24)	0.0103	0.0011	0.0634	0.0129
	(24-36)	-0.0140	0.0011	0.0265	0.0061
	(36-48)	-0.0095	0.0011	0.0144	0.0045
	(48-60)	-0.0012	0.0009	0.0140	0.0034
	(60-360)	-0.0118	0.0001	0.0050	0.0003
FICO by LTV					
FICO group	LTV group				
Missing	(0-80)	-0.1466	0.0362	0.8389	0.2286
Missing	(80-90)	-0.0609	0.0420	1.2158	0.2373
Missing	(90-100)	-0.2149	0.0412	1.6709	0.2245
(300-620)	(0-60)	-0.2986	0.0304	0.5564	0.2175
(300-620)	(60-80)	-0.3831	0.0296	1.3045	0.2155
(300-620)	(80-90)	-0.3722	0.0344	1.5808	0.2173
(300-620)	(90-100)	-0.3787	0.0334	1.7017	0.2183
(620-660)	(0-60)	-0.2092	0.0296	0.2419	0.2170
(620-660)	(60-80)	-0.2746	0.0294	1.1488	0.2153
(620-660)	(80-90)	-0.2881	0.0296	1.4439	0.2154
(620-660)	(90-100)	-0.2823	0.0304	1.5045	0.2156
(660-700)	(0-60)	-0.0885	0.0294	-0.1440	0.2168
(660-700)	(60-80)	-0.1239	0.0294	0.9297	0.2153
(660-700)	(80-90)	-0.1461	0.0293	1.2725	0.2167
(660-700)	(90-100)	-0.1366	0.0293	1.3135	0.2153
(700-740)	(0-60)	0.0184	0.0295	-0.4725	0.2181
(700-740)	(60-80)	0.0020	0.0294	0.6555	0.2153
(700-740)	(80-90)	-0.0220	0.0293	0.9694	0.2155
(700-740)	(90-100)	-0.0186	0.0293	1.0823	0.2156
(740-900)	(0-60)	0.1174	0.0293	-1.1756	0.2181
(740-900)	(60-80)	0.1357	0.0294	0.1528	0.2155
(740-900)	(80-90)	0.0932	0.0293	0.6003	0.2158
(740-900)	(90-100)	0.0703	0.0294	0.7393	0.2157
Unemployment rate (piecewise linear)	(0%-5%)	0.0534	0.0206		
	(5%-6%)	0.6895	0.0116		
	(6%-7%)	-0.4400	0.0144		
	(7%-9%)	0.2456	0.0111		
	(9%-high)	0.0656	0.0160		
% change yr ago in FHFA HPI (piecewise linear)	(low to -10%)				
	(-10% to -5%)	8.9491	1.2186		
	(-5% to 0%)	10.9583	0.3622		
	(0% to 5%)	7.5274	0.2363		
	(5% to high)	4.3971	0.1811		
% change in FHFA HPI from origination		0.5572	0.0185		
Change in 10-yr Treasury rate from origination		-0.2625	0.0035		
% change in FHFA HPI from origination (piecewise linear)	(low to -10%]			-4.8353	0.6051
	(-10% to -5%]			-7.9061	0.7941
	(-5% to 0%]			-1.5449	1.1858
	(0% to 5%]			-7.7625	1.1039
	(5% to high)			-0.5246	0.0716
Intercept		-7.6771	0.1063	-10.2707	0.6384

Source: Moody's Analytics

Chart 6

Dec-04 Unemployment Forecast

Unemployment rate, %

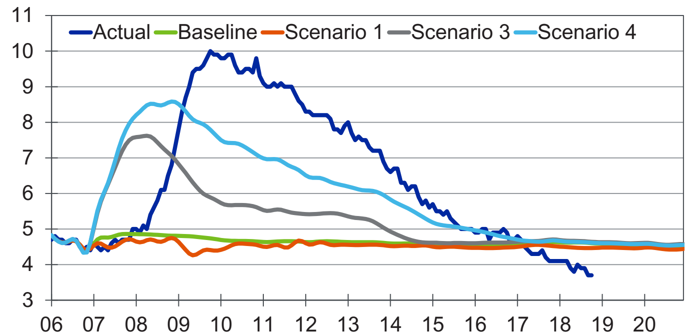


Sources: BLS, Moody's Analytics

Chart 7

Dec-06 Unemployment Forecast

Unemployment rate, %

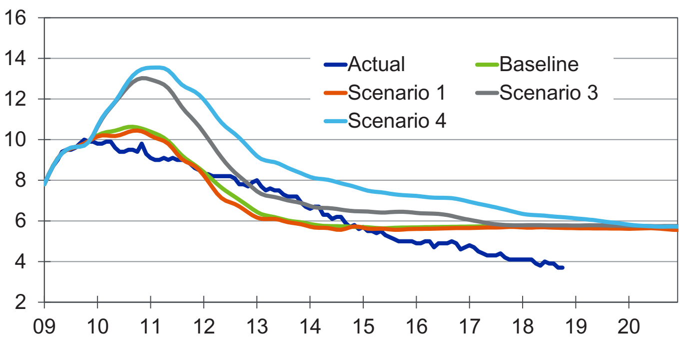


Sources: BLS, Moody's Analytics

Chart 8

Dec-09 Unemployment Forecast

Unemployment rate, %

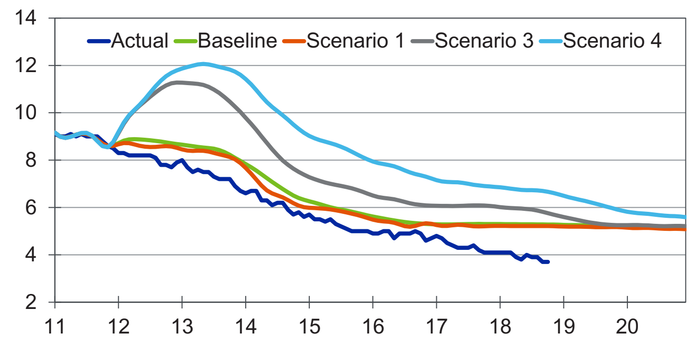


Sources: BLS, Moody's Analytics

Chart 9

Dec-11 Unemployment Forecast

Unemployment rate, %

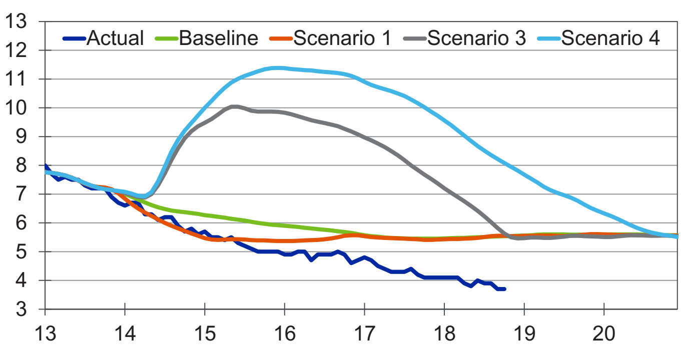


Sources: BLS, Moody's Analytics

Chart 10

Dec-13 Unemployment Forecast

Unemployment rate, %



Sources: BLS, Moody's Analytics

The alternative scenarios for each of the forecast start dates are illustrated in Charts 6 to 10. Several features of the forecasts are notable. Starting with the December 2004 forecasts, the baseline scenario was more pessimistic than the realized path of unemployment from January 2005 to January 2008, although it did not anticipate the sharp increase in unemployment after this time. The more pessimistic scenarios, Scenarios 3 and 4, also undershot the magnitude of the increase in unemployment, suggesting that the Great Recession was closer to a 98th or 99th percentile event rather than the 96th percentile consistent with Scenario 4.

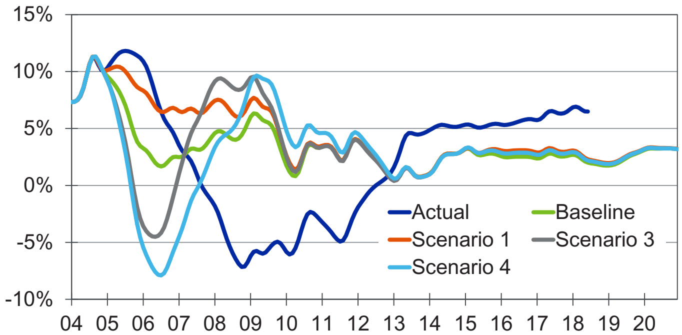
While one may jump to the conclusion that underpredicting the severity of the downturn would necessarily lead to an underprediction of loan losses, it is important to note differences in the timing of the scenarios. In estimating credit losses, an increase in unemployment may not translate into higher defaults due to the competing effect of seasoning. To emphasize the point, imagine that the unemployment rate rose to 15% in 2020. The impact on the December 2004 portfolio would have been minor given that most mortgages would have paid off or defaulted well before that time.

The December 2006 scenarios follow a similar pattern, although unemployment in the baseline was more optimistic than realized all the way until 2017. The more pessimistic scenarios did not catch the actual peak, but they preceded the actual increase in unemployment.

Chart 11

Dec-04 House Price Forecasts

FHFA All-Transactions Home Price Index, % change yr ago

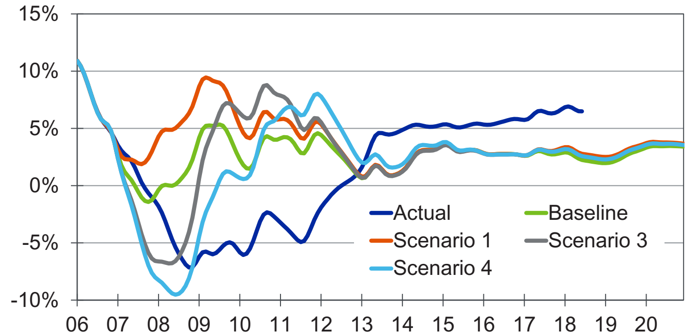


Sources: BLS, Moody's Analytics

Chart 12

Dec-06 House Price Forecasts

FHFA All-Transactions Home Price Index, % change yr ago

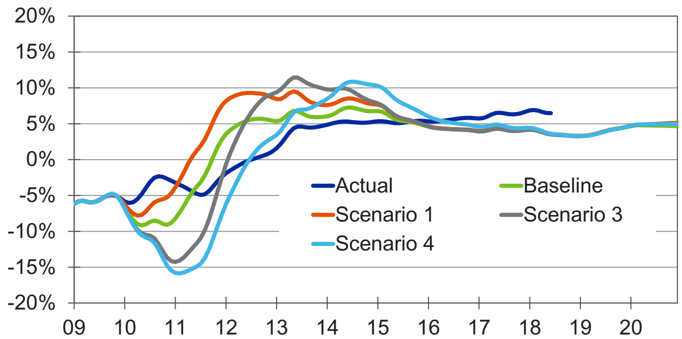


Sources: BLS, Moody's Analytics

Chart 13

Dec-09 House Price Forecasts

FHFA All-Transactions Home Price Index, % change yr ago

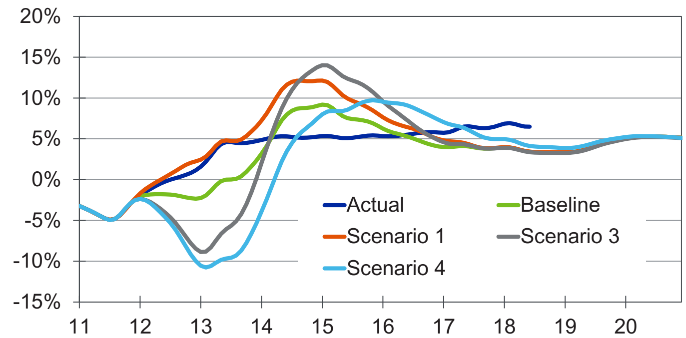


Sources: BLS, Moody's Analytics

Chart 14

Dec-11 House Price Forecasts

FHFA All-Transactions Home Price Index, % change yr ago



Sources: BLS, Moody's Analytics

The December 2009 baseline scenario was close to what was realized, although it was initially more pessimistic with a somewhat higher peak unemployment rate. The baseline then turned more optimistic, with unemployment falling faster than actual during the economic recovery. The pessimistic scenarios show significant signs of overshooting with peak unemployment rising as high as 13%.

A loss estimate based on either of these two scenarios would have significantly overshot actuals, which may lead some to conclude that CECL procyclicality would follow. But two important considerations are needed. First, CECL is not a stress-testing exercise. The loss estimates are intended to be management's best judgment of future expected losses. Some consideration of the pessimistic scenarios would be prudent given the uncertainty inherent in any single economic forecast as we discuss in the sections that follow, but complete dependence on these scenarios would not be appropriate. Moreover, users should note the risk compression inherent in the scenarios. Whereas the unemployment rate rose from approximately 5% to 10% during the Great Recession, the severe recession in Scenario 4 has unemployment rising by only 3 percentage points. Given the business cycle, the deeper the economy gets into a downturn, the lower the downside risks and the greater the upside risks.

The December 2011 scenarios were similar to the December 2009 scenarios, although unemployment in the baseline scenario was somewhat higher throughout the recovery period. The equilibrium level of unemployment was forecast to be higher than the actual experience.

Charts 11 to 15 compare the house price forecast scenarios for each forecast start date. We observe similar patterns of over- and undershooting as with the unemployment rate forecasts. Again, we note that the timing of declines in the alternative scenarios may have an impact on forecasted losses at different points in time.

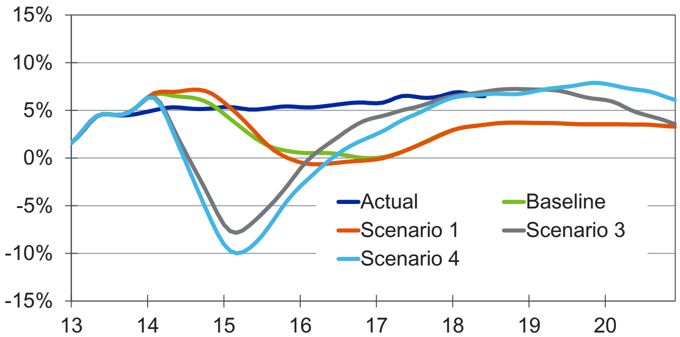
Loss simulation results

Given the economic scenarios, we then created a dataset with the active set of Freddie Mac mortgages outstanding at each forecast start date. That is, we create a snapshot of mortgages as of the reporting date removing any previous loan defaults and payoffs as well as any future originations. We grouped the loans into the same origination vintage by credit score and LTV cohort that we used to develop our mortgage default and prepay-

Chart 15

Dec-13 House Price Forecasts

FHFA All-Transactions Home Price Index, % change yr ago

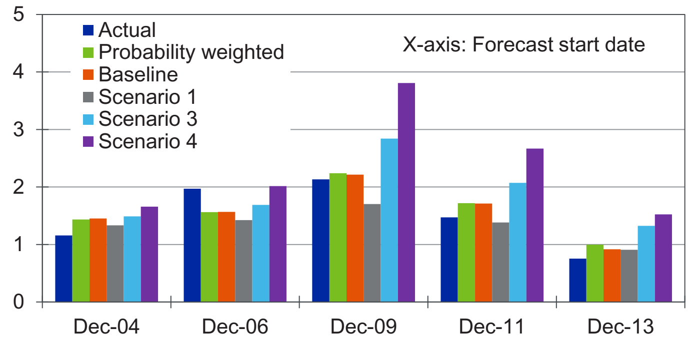


Sources: BLS, Moody's Analytics

Chart 16

Projected Losses by Scenario

Probability-weighted credit loss rate forecast, % balance



Source: Moody's Analytics

ment models. We then use the economic forecasts to forecast monthly default and prepayment rates over the remaining lifetime of each cohort in the portfolio.

Using these forecasts, we project the number of outstanding mortgages, prepayment and defaults based on the following recursive formulas:

Activet = # Activet-1 – # Defaultt – # Prepayt\

Prepayt = # Activet-1 * Probability of Prepaymentt

Defaultt = # Activet-1 * (1 – Probability of Prepaymentt) * Probability of Defaultt

Finally, we summed up the forecast number of defaults in each future time period to compute the projected lifetime number of defaults for each cohort and for the aggregate portfolio. Dividing this number by the number of loans observed at the start of the forecast gives us the cumulative probability of default or PD rate.

To compute the expected credit loss for each portfolio, we multiply this probability of default by the exposure at default, or EAD, and loss given default, or LGD, rate based on the formula:

ECL = EAD * PD * LGD

To simplify our analysis for expositional purposes, we assumed the EAD to be equal to the outstanding unpaid balance at the start of the forecast period. To the extent loans may have amortized before defaulting, this assumption may slightly overstate the true EAD. Given that most loans default at an early age when the amount of loan balance amortization is small, this assumption likely has a minor impact.

We assumed a constant of 35% for the loss given default rate. In reality, LGD fluctuates with changes in house prices as well as lender policies regarding foreclosures, short sales, and other loss mitigation efforts. Given that the range of LGD rates is not large across the economic cycle, we use a fixed constant rather than complicate the analysis further. Relaxing this assumption does not change our qualitative findings.

The results of our analysis are provided in Chart 16 for each of the forecast start dates. We compare the 10-year expected credit loss projections across our four scenarios with the actual realized loss rate through December 2017.[7]

Our key findings are:

Consistent with our inability to completely foresee economic turning points, our loan loss forecasts over- and undershoot at different points in the cycle. In 2004, our baseline scenario was too pessimistic pushing predicted losses higher than actually realized. Conversely, in 2006 our baseline was too optimistic leading to underprediction of lifetime defaults. Consistent with our intuition, we observed the ordering of losses across the upside and downside scenarios that we would expect. Given nonlinearities in the response of defaults to economic weakness, we observe large increases in default projections for our most pessimistic economic scenarios.

We included a probability weighted scenario for each forecast period by assigning the baseline scenario a 60% weight, Scenario 1 a 20% weight, and Scenario 3 a 20% weight.[8] This is consistent with how we believe most banks will actually implement CECL.

Using the 90+ day delinquency rate as a proxy for loss reserves under the incurred loss standards, we observe the fluctuations in our CECL forecasts due to under- and overshooting are less pronounced than the runup in delinquencies during the Great Recession (see Chart 1). This supports our conclusion that CECL will not be countercyclical, but will be meaningfully less procyclical than the current incurred loss standard.

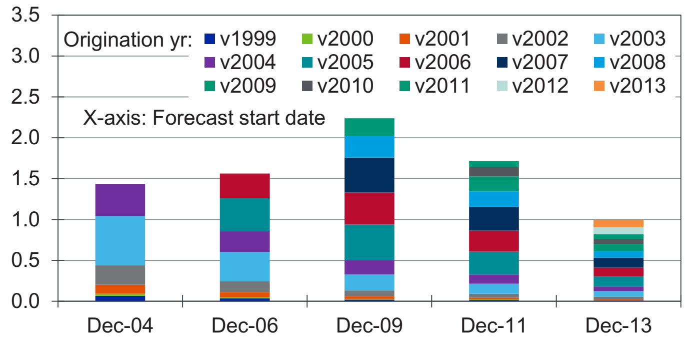
Another key finding is that procyclicality should be considered within the context of origination vintages. Under CECL, the overall loss reserve in a given period could vary because of lending decisions during the period as well as changes in the economic forecast. If CECL reserves increase simply because a lender did a lot of lending, that is not evidence of loss reserve cyclicality. Optimally, CECL will act as a countercyclical buffer that leads to less lending in a boom and more lending in a downturn.

Chart 17 decomposes our probability weighted CECL forecast of lifetime losses

Chart 17

Projected Losses by Origination Vintage

Probability-weighted credit loss rate forecast, % balance



Source: Moody's Analytics

by origination vintage starting at each of our five reporting periods. Examination of the estimates provides additional evidence of the reduced procyclicality within each origination vintage. For example, the lifetime projection for 2004 originations was highest in 2004, but fell in subsequent periods. The loans were already mature when house prices fell in 2006, muting the impact. Forecasted losses for the 2006 vintage rose sharply from 2006 to 2009 given the surprisingly severe recession. While a sizable increase, it was much smaller than what we observed for the 90+ day delinquency rate for the same cohort.

Focusing on the forecasts for the 2009 book, nearly one-third of the loss estimate is attributable to loans originated in 2007, 2008 and 2009. Without these vintages, the estimated CECL reserves would have fallen as the rise in losses for 2006 originations was offset by the decrease in losses from older loans. While this additional lending would not have been eliminated under CECL, the rise in loss reserves from 2004-2006 would have hit the bottom line and presumably curbed at least some of the lending in these vintages before the economy went into recession. This shift in lending behavior during the boom would further reduce CECL's procyclicality.

Big step forward

CECL represents a sea change in financial accounting, and its implementation will be a challenge. Lenders rightly worry about the imprecision of economic forecasts and the impact they might have on their CECL estimates. As shown in our analysis, economic forecasts can have a material impact on loss estimates. Forecast uncertainty can lead to under- or overprediction at different points in the cycle.

However, the CECL guidelines provide lenders the discretion needed to address this issue. Forecasting losses under multiple scenarios reduces the volatility that could result from using a single forecast that is subject to large revisions. While CECL requires a lifetime loss estimate, it permits lenders to calculate this estimate based on a forecast of performance over a "reasonable and supportable" horizon plus an agnostic "reversion" period. An institution that feels uncomfortable with its ability to forecast far off into the future can choose a short "reasonable and supportable" period. Although this assumption may bring CECL estimates closer to incurred losses, the origination lifetime loss concept under CECL will still frontload more of the loss estimate relative to the incurred loss method.

The treatment of capital is another thorny issue—if loss reserves increase under CECL, then it stands to reason that bank regulators should adjust banks' capital requirements. However, the Federal Reserve has already agreed to provide banks with a transition period to minimize financial system disruptions when CECL is adopted starting in 2020. The Fed has also requested additional public comment, suggesting that additional regulatory changes may be forthcoming to address this criticism.

CECL is not a panacea. It will not prevent speculation and bad loans from being made. Lenders will still be tempted to estimate losses short of what they have experienced historically or what their models project. But CECL is a big step in the right direction. It will provide additional insight into the lending decisions and risks taken by financial institutions. Since CECL more closely aligns underwriting decisions with loss reserving, it will reduce the odds of another financial crisis and Great Recession.

Endnotes

1 See "CECLnomics and the Promise of Countercyclical Loss Accounting," Cristian DeRitis, Moody's Analytics white paper, September 2018.

2 We note that setting allowances for loan and lease losses under the incurred loss standard involves a mixture of historical data analysis and management judgment, including consideration of current conditions. As such, historical incurred loss estimates for the specific mortgage portfolio we examined—a subset of Freddie Mac's total book of business—are not available. We use the 90+ day delinquency rate on this portfolio as a reasonable approximation of the pattern of incurred losses given its high correlation with the loss allowance rates shown in Chart 2.

For context, Freddie Mac's reported loan loss reserves for its entire single-family mortgage portfolio rose from $520 million to $33 billion from 2005 to 2009 as shown in the table below. Correlation between the loss reserve and the 90+ day delinquency rate is in excess of 99% (see Appendix).

3 The relationship between the credit and economic cycle varies based on the performance measures and the asset classes being considered. For example, residential mortgage defaults are highly correlated with house prices, while credit card defaults are more correlated with unemployment or personal income growth.

4 See "Current Expected Credit Loss: Lessons from 2007-2009," Francisco Covas and William Nelson, Bank Policy Institute, July 2018. Also see "CECL Procyclicality: It Depends on the Model," Joseph Breeden, August 2018.

5 The FICO credit score was binned into these ranges: (300-620), (620-660), (660-700), (700-740), (740-900). Origination combined LTV ratios were binned into these ranges: (0-60), (60-80), (80-90), (90-95), (95-100).

6 For an overview of the Moody's macroeconomic model methodology please see https://www.economy.com/home/products/samples/macromodel.pdf

7 Note that this does lead to a potential inconsistency given that the 2009 and 2011 forecasts have a shorter window for realized defaults. Given expectations for continued growth in house prices and the seasoning of loan portfolios, the actual default rates are unlikely to rise materially above their levels through 2017.

8 For additional information on weighting scenarios for CECL and how the use of multiple scenarios may provide a more accurate and less volatile forecast over time, please see the white paper "Beyond Theory: A Practical Guide to Using Economic Forecasts for CECL Estimates".

Appendix: Freddie Mac Loan Loss Reserves and Delinquency Rates

Reporting yr	Single-family loan loss reserve, $ mil	Loss reserve, % of total mortgage portfolio	90+ day delinquency rate, % of total mortgage portfolio
2005	520	0.04	0.53
2006	592	0.04	0.42
2007	2,760	0.16	0.65
2008	15,341	0.81	1.72
2009	33,026	1.69	3.87

Sources: Freddie Mac Annual 10-K filings, Moody's Analytics

About the Authors

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.

Mark Zandi is chief economist of Moody's Analytics, where he directs economic research. Moody's Analytics, a subsidiary of Moody's Corp., is a leading provider of economic research, data and analytical tools. Dr. Zandi is a cofounder of Economy.com, which Moody's purchased in 2005.

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A trusted adviser to policymakers and an influential source of economic analysis for businesses, journalists and the public, Dr. Zandi frequently testifies before Congress on topics including the economic outlook, the nation's daunting fiscal challenges, the merits of fiscal stimulus, financial regulatory reform, and foreclosure mitigation.

Dr. Zandi conducts regular briefings on the economy for corporate boards, trade associations and policymakers at all levels. He is on the board of directors of MGIC, the nation's largest private mortgage insurance company, and The Reinvestment Fund, a large CDFI that makes investments in disadvantaged neighborhoods. He is often quoted in national and global publications and interviewed by major news media outlets, and is a frequent guest on CNBC, NPR, Meet the Press, CNN, and various other national networks and news programs.

Dr. Zandi is the author of *Paying the Price: Ending the Great Recession and Beginning a New American Century*, which provides an assessment of the monetary and fiscal policy response to the Great Recession. His other book, *Financial Shock: A 360º Look at the Subprime Mortgage Implosion, and How to Avoid the Next Financial Crisis*, is described by the New York Times as the "clearest guide" to the financial crisis.

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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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