Finance and Economics Discussion Series
Divisions of Research & Statistics and Monetary Affairs
Federal Reserve Board, Washington, D.C.

The Impact of the Current Expected Credit Loss Standard (CECL) on the Timing and Comparability of Reserves

Sarah Chae, Robert F. Sarama, Cindy M. Vojtech, and James Wang

2018-020

Please cite this paper as:
Chae, Sarah, Robert F. Sarama, Cindy M. Vojtech, and James Wang (2018). "The Impact of the Current Expected Credit Loss Standard (CECL) on the Timing and Comparability of Reserves," Finance and Economics Discussion Series 2018-020. Washington: Board of Governors of the Federal Reserve System, https://doi.org/10.17016/FEDS.2018.020.

The Impact of the Current Expected Credit Loss Standard (CECL) on the Timing and Comparability of Reserves

Sarah Chae, Robert F. Sarama, Cindy M. Vojtech, and James Wang[1]

March 6, 2018

Abstract

The new forward-looking credit loss provisioning standard, CECL, is intended to promote proactive provisioning as loan loss reserves can be conditioned on expectations of the economic cycle. We study the degree to which one modeling decision– expectations about the path of future house prices – affects the size and timing of provisions for first-lien residential mortgage portfolios. While we find that provisions are generally less pro-cyclical compared to the current incurred loss standard, CECL may complicate the comparability of provisions across banks and time. Market participants will need to disentangle the degree to which variation in provisions across firms is driven by underlying risk versus differences in modeling assumptions.

JEL codes: G21, G28, M40, M48

Key words: accounting rule change, mortgage loans, model risk

[1] Sarah Chae, Federal Reserve Board of Governors, sarah.chae@frb.gov
Robert F. Sarama, Federal Reserve Board of Governors, robert.f.sarama@frb.gov
Cindy M. Vojtech, Federal Reserve Board of Governors, cindy.m.vojtech@frb.gov
James Wang, Federal Reserve Board of Governors, james.z.wang@frb.gov

The views expressed here are those of the authors and do not necessarily reflect the positions of the Federal Reserve Board of Governors or the Federal Reserve System.

1. Introduction

U.S. Generally Accepted Accounting Principles (U.S. GAAP) is a common set of financial accounting and reporting standards established to create financial reports that provide information to investors and other users of financial reports. The Financial Accounting Standards Board (FASB) is responsible for developing and issuing these standards, one of which is the focus of this paper addressing how institutions establish an allowance for loan and lease losses (ALLL). Recently, that standard has changed in ways that will meaningfully affect how banks and financial institutions manage and report ALLL.

For the past 40 years, banks in the United States have used the incurred loss standard to calculate their ALLL. Under the incurred loss standard, credit losses cannot be recognized until it is probable a loss event has occurred. In simple terms, a loss is incurred if it is probable a loan's risk characteristics have deteriorated as of the balance sheet date – events beyond the balance sheet date cannot be considered. Therefore, the incurred loss standard hinders banks' ability to build and manage ALLL during the early stages of an economic downturn. The delayed recognition of losses can result in significant, rapid, and volatile increases in provisions (with corresponding reductions in regulatory capital) in the midst of a recent downturn. That is, the standard is pro-cyclical in that it can result in an overstatement (understatement) of ALLL relative to expected losses at the trough (peak) of an economic cycle.

Pro-cyclicality of the incurred loss standard, which can result in ALLL being "too little too late," motivated the FASB to re-examine the incurred loss standard. In June 2016, FASB issued its revised ALLL standard as the current expected credit loss standard (CECL). Under CECL, when a bank originates a loan, the total expected credit losses over the contractual life of the exposure are also recognized. CECL requires a forward-looking approach that would allow for ALLL to build in anticipation of expected losses and earlier than under the incurred loss standard. As a result, CECL should be less pro-cyclical. However, determining expected losses requires risk managers to make subjective assumptions about future conditions, which could hinder the comparability of ALLL across banks and time to market participants.

Among those assumptions, risk managers will have to set expectations regarding future economic conditions that affect loan losses. In this paper, we use a stylized framework to study the degree to which one such macroeconomic assumption – the future path of house prices –

affects the size and timing of ALLL for first-lien residential mortgages under CECL. We find that CECL generally achieves its goals of being less pro-cyclical than the incurred loss standard although the degree of pro-cyclicality can vary significantly for seemingly small differences in assumptions about future house prices. Variation in ALLL directly affects bank capital which in turn influences the allocation of credit. Specifically, there is an extensive literature on bank capital and lending that suggests that if CECL could be less pro-cyclical, banks would have additional capital to support lending during a financial downturn. [2]

Modeling assumptions could also complicate the comparability of provisions across banks and time. Market participants such as investors and analysts rely on disclosed provisioning and ALLL data to assess underlying portfolio risk. Under the incurred loss standard, higher provisioning levels correspond directly to increased losses. By incorporating somewhat opaque, bank-specific idiosyncratic modeling decisions, the tight link between ALLL and actual losses may be relaxed – high risk portfolios under optimistic expectations could be confounded with low risk portfolios with more conservative expectations. Market participants could face difficulty in disentangling the degree to which variation in ALLL is driven by modeling assumptions as opposed to differences in underlying risk.

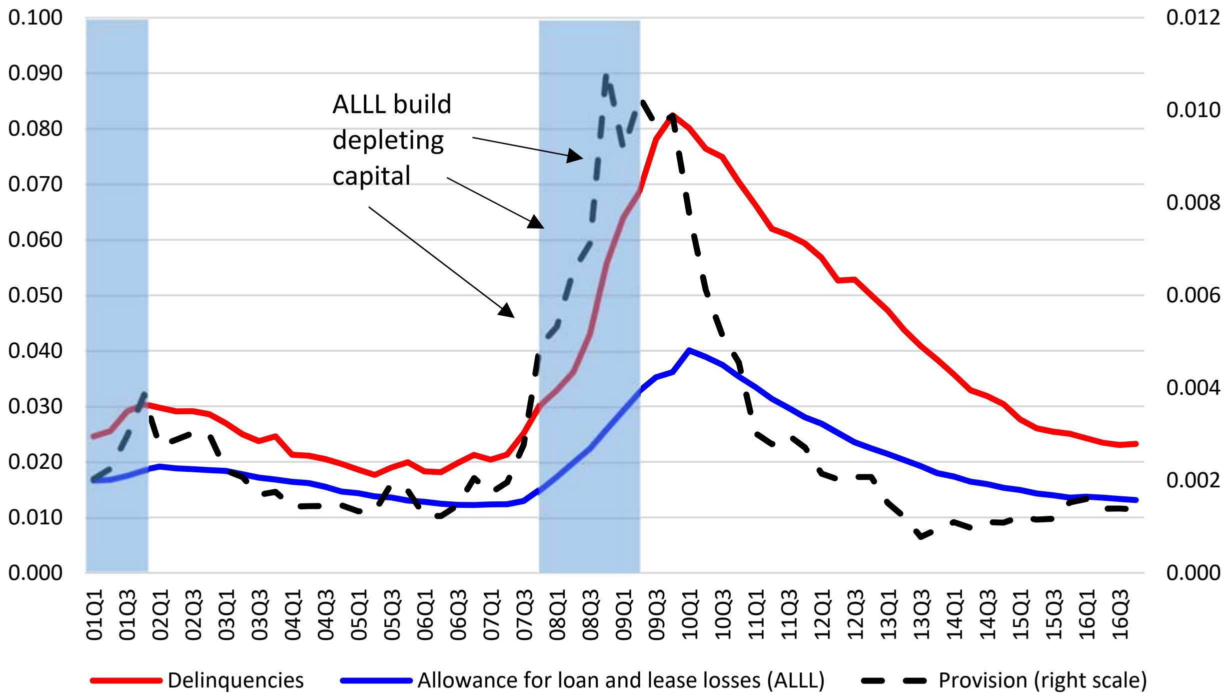
The next section provides more background on the new accounting standard. In section 3, our empirical framework is presented and tested. Section 4 concludes.

2. CECL Overview

Figure 1 highlights the “too little too late” issue by showing what happened to primary measures of total loan losses at bank holding companies (BHCs) between 2000 and 2016. Delinquent loans as a share of total assets (red line) began to increase in 2007 and almost concurrently with provisions (dashed black line). With the economic downturn shaded in blue, most of the buildup in ALLL happened *during* the recession when BHCs’ cash flow and earnings were most stressed. ALLL (blue line) did not peak until 2010, almost a year after the official end of the recession. During this period, bank capital continued to be stressed by the elevated provisioning buildup.

[2] See for example, Bernanke and Lown (1991), Kishan and Opiela (2000), Francis and Osborne (2009), Berrospide and Edge (2010), Cornett, McNutt, Strahan, and Tehranian (2011), and Carlson, Shan, and Warusawitharana (2013).

Figure 1: Delinquencies, ALLL, and Provisions as a Percent of Total Assets, Bank Holding Companies, 2000-2016



Source: Federal Reserve Board, Form FR Y-9C, Consolidated Financial Statements for Bank Holding Companies.
Note: Delinquent loans are defined as loans that are more than 30 days past due or are in nonaccrual status. The blue shading shows periods of recession as defined by the National Bureau of Economic Research.

Following the recent financial crisis, many agencies, financial institutions, and market participants requested reviews of the accounting rules.[3] In response, both the FASB and the International Accounting Standards Board (IASB) issued new expected credit losses standards.[4] In July 2014, the IASB issued IFRS 9, IASB's new expected credit losses standard, and in June, 2016, FASB issued CECL.[5] CECL and the IFRS 9 differ along several dimensions. Most notably, IFRS 9 is a staged approach in that only a portion of the overall loan portfolio is required to hold lifetime expected credit losses (generally, performing assets are required to carry

[3] For example, at the London G20 summit in April 2009, the leaders called for accounting standard setters to "strengthen accounting recognition of loan-loss provisions by incorporating a broader range of credit information." (link) Additionally, in remarks to the Congressional Financial Crisis Inquiry Commission in January 2010, the Chairman and CEO of JPMorgan Chase, Jamie Dimon, faulted the incurred loss standard for "caus[ing] reserves to be at their lowest levels at a time when high provisioning might be needed the most." (link)
[4] Refer to FASB's June 6, 2016 news release (link) and IASB's project summary (link) for additional background information.
[5] For most institutions applying IFRS 9, the standard is effective beginning January 2018. For institutions applying CECL, the standard is effective in 2020 for SEC filers and 2021 for non-SEC filers.

only 12 months of expected credit losses), whereas CECL requires lifetime expected credit losses to be held for all loans.[6]

2.1 ALLL under CECL

CECL is applicable to all financial assets carried at amortized cost (e.g., held-for-investment (HFI) loans and held-to-maturity (HTM) securities). Roughly 60 percent of total assets across bank holding companies (BHCs) are comprised of HFI loans and HTM securities (2016:Q4). In this paper, we primarily model the treatment of CECL for the loan book.

CECL changes the measurement of credit losses from an incurred loss methodology to an expected credit loss methodology by requiring financial institutions to 1) use information that is more forward-looking and 2) recognize the lifetime expected credit losses as of the reporting date for all eligible financial assets including newly originated or acquired assets. Under CECL, the ALLL is a valuation account, measured as the difference between the financial assets' amortized cost basis and the net amount expected to be collected on the financial assets.

In determining the net amount expected to be collected, institutions are required to use information about past events, current conditions, and *reasonable and supportable forecasts* (i.e., forward-looking information) relevant to assessing the collectability. The FASB does not prescribe a specific method in determining the reasonable and supportable forecast period, but specifies that for periods beyond the "reasonable and supportable" forecast period, institutions are required to revert back to historical loss information that reflects the contractual term of the financial instrument(s).[7]

The FASB wrote the CECL guidance as a principles based accounting standard to ensure that the standard is scalable to institutions of all sizes and complexity. As such, CECL does not specify a

---

[6] Another difference is that IFRS 9 contains a trigger that increases ALLL from expected losses over 12 months to lifetime in the event of probable losses.

[7] The relevant language in the standard is the following:

> "However, an entity is not required to develop forecasts over the contractual term of the financial asset of group of financial assets. Rather, for periods beyond which the entity is able to make or obtain reasonable and supportable forecasts of expected credit losses, an entity shall revert to historical loss information determined in accordance with paragraph 320-20-30-0 that is reflective of the contractual term of the financial asset or group of financial assets. An entity shall not adjust historical loss information for existing economic conditions or expectations of future economic conditions for periods that are beyond the reasonable and supportable period."

method for measuring expected credit losses and allows financial institutions to choose methods that reasonably reflects its expectations of the credit loss estimate.

2.2 Sources of Variation in ALLL under CECL

ALLL reported by banks in their financial reports provides markets with information about the riskiness of the loans held by the banks. However, CECL introduces a number of other sources of variation in the calculation of ALLL that may cloud that information and make comparisons across banks and time more difficult.

Some sources of variation will be quite familiar to risk modelers. Risk modelers at banks, as part of the origination process, have long had to develop methods to map portfolio characteristics to losses under static economic conditions. Portfolio characteristics such as geographic concentration or borrower financials have a long history in credit risk modeling, and their relationship with losses and provisioning is also well understood by bank examiners and market participants alike. In other words, the market has significant experience with inferring the underlying credit risk of a portfolio given its risk characteristics and recent changes in ALLL.

However, the requirements under CECL are different in that the models used in CECL require estimates of *lifetime losses* under reasonable and supportable *forecasts of economic conditions*. Taken at face value, that requirement means that risk modelers will have to develop projections of economic conditions to use as inputs into the expected loss models. These projections add a potential confound into the relationship between portfolio risk and changes in ALLL. It is that source of variation, requiring subjective, bank-specific idiosyncratic modeling choices, less common in current financial reporting, that is the subject of this paper.

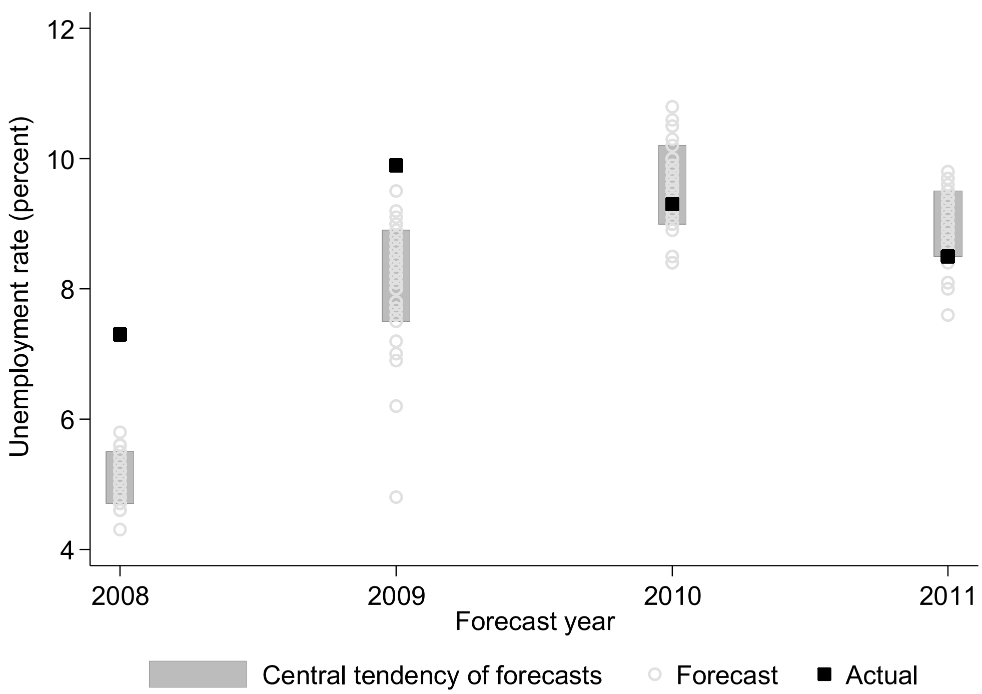
2.3 Uncertainty in Macroeconomic Forecasts

There are many challenges associated with forecasting that contribute to substantial disagreement among macroeconomic forecasts. Some challenges are related to changes in the structure of the macroeconomic environment, others derive from issues associated with the real-time measurement of the data that are the inputs of the forecasts.[8] Others still, are driven by forecaster biases that may be behavioral or rational (see Batchelor and Dua 1990).

[8] Orphanides and van Norden (2002) show that complications associated with the measurement of the output gap make it difficult to forecast the output gap in real time.

These challenges exist even among professional forecasters. Figure 2 shows that 1-year ahead forecasts, sourced from the Wall Street Journal Economic Forecasting data, exhibit significant disagreement. For example, the December 2008 forecasts of the December 2009 unemployment rate ranged from under 5 percent to almost 10 percent, with a central tendency between 7 percent and 9 percent. The actual unemployment rate in December 2009 was just under 10 percent, well outside of the central tendency. The survey participants include many of the risk analysts at banks and consultancies who we might expect to contribute forecasts for financial reporting under CECL. This variation in forecasts motivates one of our empirical results, which is that while CECL may be generally less pro-cyclical, modeling assumptions may hinder comparability across banks and time.

Figure 2: Variation and error in unemployment rate forecasts



Source: Wall Street Journal, "Economic Forecasting Survey," http://projects.wsj.com/econforecast/
Notes: Forecasts and actual figures are predicted for December of a given year and were made the prior December. The central tendency is defined as the 10th percentile to 90th percentile range.

3. Empirical Investigation

In order to empirically evaluate the sensitivity of modeling assumptions on ALLL and to minimize the effect of portfolio-level idiosyncrasies, we confine our empirical investigation to first-lien mortgages. We focus our analysis on mortgages instead of a broader snapshot of the bank's loan book to better explain the underlying data. First-lien mortgages are extensively studied with well-documented relationships between risk drivers and macroeconomic factors. This narrow focus reduces the likelihood that our results are confounded by model fit or misspecification.

Our empirical analysis proceeds in two stages. First, we develop a simple mortgage default and prepayment model that conditions loan-level losses on the path of county-level home prices. Our stylized yet robust model captures the key determinants of mortgage default, and the simple framework allows for straightforward counterfactual analysis under different forecast assumptions for future home prices. One forecast that we investigate is a perfect foresight model where we use the actual path of home prices to show that CECL, with perfect foresight, leads to more forward-looking and less pro-cyclical provisioning than the incurred loss standard.[9]

In the second part of the analysis, we seed our mortgage model with counterfactual price patterns for home prices reflecting different expectations about future conditions. While risk managers must make assumptions along hundreds of modeling dimensions, in this paper we focus on three broad types of forecast methodology: optimistic, continuation of recent trends, and a limited foresight assumption. Each affects expected losses and the degree of pro-cyclicality differently, reflecting the variation in ALLL that may arise from different modeling assumptions.

3.1 Data

Our mortgage data comes from a 1 percent sample of the LPS McDash mortgage servicing data. In order to further reduce the complexity of modeling credit risk for different types of assets, our analysis of the effect of CECL will focus on a sample of homogenous loans with similar risk characteristics: 30-year fixed-rate first-lien mortgages that were originated in California between

---

[9] Here we rely on the FASB characterization where pro-cyclicality means "overstated reserves at the trough of a cycle and understated reserves at the peak of a cycle."

2002 and 2015. California is the nation's largest housing market and the state experienced a statewide HPI decrease of roughly 40 percent during the 2008 financial crisis. The extended time series available in the servicing data allows us to estimate over an entire housing market cycle to approximate the impact of a downturn on mortgage defaults. That dataset of California mortgages contains 47,517 mortgages of which 30,099 (63 percent) prepay and 2,690 (5.7 percent) end in loan default. The remainder are still current as of the last reported date of December 2015.

3.2 Mortgage Default Model

Because CECL does not prescribe specific credit loss models and provides a great deal of latitude in modeling choices, we focus on a standard, stylized loan-level mortgage default model. The model forecasts default and prepayment outcomes given the expected path of home prices and initial credit scores in a competing hazards framework. One of its main strengths is its simplicity and sparseness, which allows us to more easily work with alternative counterfactual home prices. Additionally, by restricting our analysis to a relatively homogenous loan population, our stylized model should still have sufficient richness in describing the underlying data.

The theoretical underpinning of the model is a reduced form approximation of the household default and prepayment decision. [10] The framework is a discrete-time hazard model that tries to determine the probability of surviving, or staying current, each month of the loan's entire contractual payment period. Each period, borrower i has a time-varying hazard associated with both default $H_i^D(t)$ and prepayment $H_i^P(t)$. The survival function $s_i(t)$ for this borrower of surviving t periods without default or prepayment is given by

$$s_i(t) = \prod_{n=1}^{t} (1 - H_i^D(n) - H_i^P(n)) \tag{1}$$

Estimation proceeds by maximum likelihood. To form the likelihood, note that the probability of default in period t given survival until period $t-1$ is given by $PD_i(t) \ = \ H_i^D(t) * s_i(t-1)$ so that the likelihood function is the product of $PD_i(t)$ for each borrower i.

[10] Examples of other papers that have used hazard models to estimate mortgage default are Deng, Quigley and van Order (2000); Clapp, Goldberg, Harding, and LaCour-Little; Deng and Gabriel (2006); Clapp, Deng, and An (2006); de Servigny and Joobst (2007); Demyanyk and Van Hemert (2007); Foote, Gerardi, and Willen (2008); Tracy and Wright (2012)

We parameterize the default and prepayment hazard functions into two components: a baseline hazard that accounts for temporal seasoning effects as well as a loan-level hazard modeling loan-level risk drivers. We specify the baseline hazard using fixed effects for each payment month up to 120. This allows each payment month to have its own payment and default rate, thereby providing a flexible treatment of repayment patterns across time.

$$H_i^j(t) = f_i^j(LTV, Credit\ Score) \times \sum_{s=1}^{120} \alpha_s^j \mathbf{1}\{s = t\}\ for\ j = D, P \tag{2}$$

The loan-level hazards $f_i^D(\cdot)$ and $f_i^P(\cdot)$ are parameterized to be dependent on the borrower's credit score at origination and the loan's loan-to-value (LTV) ratio. Credit scores at origination capture borrower risk factors that proxy for the borrower's ability to repay – borrowers with weaker credit scores are those that tended to have difficulty repaying loans and may also have difficulty in the future. We use 12 categories of fixed effects for credit scores representing FICO ranges from less than 600 to 780 or more. The approach allows for nonlinear responses of repayment as a function of individual credit scores. LTV captures the degree to which the borrower will be incentivized to exercise his or her implicit option to put the collateral back to the bank in exchange for extinguishing the loan.

We estimate two separate LTV hazards: one that utilizes LTV at origination and another with the current, refreshed LTV to examine how the underlying collateral value responds to both initial conditions and changes in the macroeconomic environment. Refreshed LTV is constructed as the last observed unpaid principal balance on a loan divided by an updated property value. The updated property value is calculated by scaling the origination home price by the gross growth rate in local county home prices since origination. If expectations of home prices rise, refreshed LTV decreases. See Appendix A for the outcome of the hazard regressions.

While other factors are important when modeling mortgage default such as geographic controls, unemployment, interest rates, as well as origination year, our set of sparse controls already captures roughly 50 percent of the variation in default as measured by simple R-squared. Additionally, we avoid potential collinearity in not including further correlated factors due to the degree of co-movement in housing prices, unemployment, and interest rates.

The two loan-level hazards (for both default and prepayment) are given by

$$f_i^j(LTV, Credit\ Score) = \begin{cases} f\left(\dfrac{UPB_{i,t}^R}{HP_i(t)}, CREDIT\ SCORE_i^o\right)\ if\ LTV = \ Refreshed\ LTV \\ f\left(\dfrac{UPB_i^{Orig}}{HP_i^o(t = Orig\ t)}, CREDIT\ SCORE_i^o\right)\ if\ LTV = \ Origination\ LTV \end{cases} \quad for\ j = D, P$$

where $\frac{UPB_{i,t}^R}{HP_i(t)}$ is the refreshed LTV on loan *i* at time *t*, $\frac{UPB_i^{Orig}}{HP_i^o(t=Orig\ t)}$ is the origination LTV on loan *i*, and $CREDIT\ SCORE_i^o$ is the borrower's FICO credit score on loan *i* at origination. Combined with the baseline hazards, the functions $H_i^{D,r}(t)$ and $H_i^{D,o}(t)$ measure the probability loan *i* will default in period *t* based on refreshed LTV or origination LTV respectively, conditional on surviving until period *t-1*. For our counterfactual analysis, the only difference across specifications is how we vary the forecast of $HP_i(t)$.

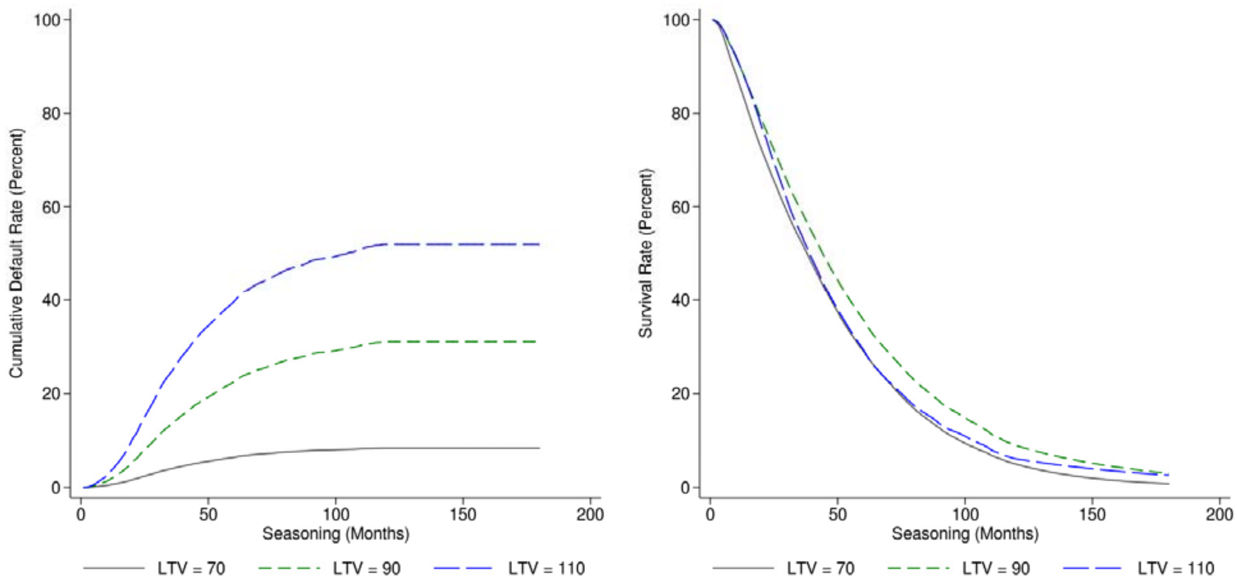
Incorporating both the origination and refreshed LTV is motivated by the CECL model's loss forecast period. Guidance indicates that banks should attempt to base their loss estimates on a "reasonable and supportable" forecast period. Outside of this period, loss estimates should revert back to the long-run experience. We interpret this guidance by forecasting expected loan losses using the current, refreshed LTV for a two year period and then reverting back to a loss rate projected only by the origination LTV outside of the two year window. The rationale is that the model estimated using the origination LTV is a "through the cycle" approach that does not rely on forecasts while the model estimated with the refreshed LTV accounts for "point in time" forecasts of near-term trends. Both the origination and refreshed LTV values are parametrized using fixed effects for each 10 percentage point change from less than 20 to 120 or more, which also treats the sensitivity of losses to LTV in a flexible fashion.

$$CDR_{i,lifetime} = \sum_{t=1}^{24} H_i^{D,r}(t) + \sum_{t=25}^{120} H_i^{D,o}(t) \tag{5}$$

The predicted cumulative default rates are then combined with a constant loss given default (LGD) assumption of 0.3 to arrive at an expected loss rate $E[Losses_{i,t}] = .3 * CDR_{i,lifetime} * UPB_{i,t}$.[11] Aggregated across all modeled mortgages, the level of ALLL is calculated as the sum from the expected losses on current mortgages plus losses on the defaulted balances.

[11] Goodman and Zhu (2015) find that the average loss severity for mortgages was 33.9%.

Figure 3: Cumulative default and survival rates, by refreshed LTV.

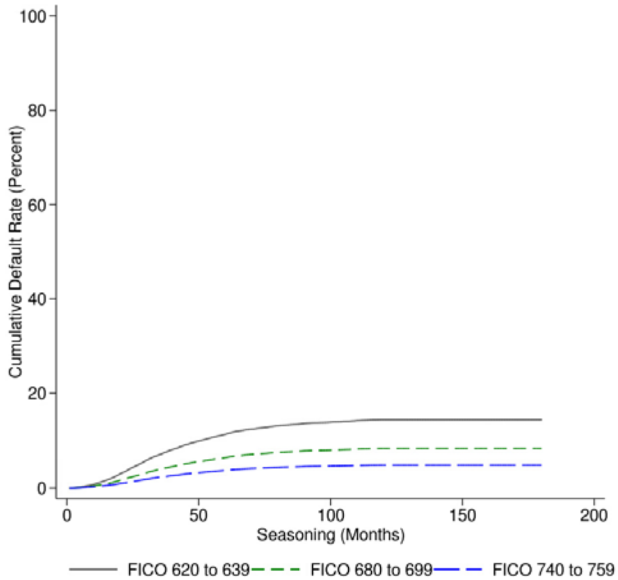


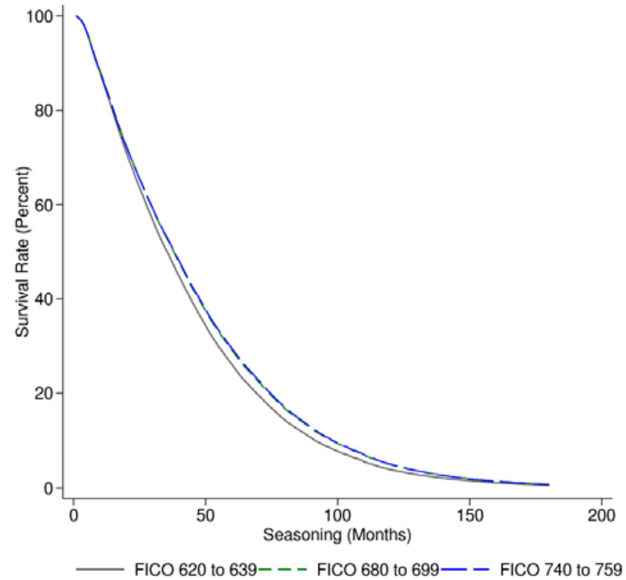
Source: Black Knight Financial Services, LPS McDash Data; and author calculations.

Note: Projections assume the credit score is from 720 to 739.

Variation in the modeled default and survival rates across LTV and credit score segments of the data are plotted in figures 3 and 4. The LTV plot gives a sense of the sensitivity of the model to house price changes: the model predicts that the cumulative default rate on a 10-year-old mortgage with a refreshed LTV of 110 is roughly double that of a similar loan with a LTV of 90. That sensitivity of mortgage default rates to fluctuations in house prices was a key feature of the 2008-2009 recession, and is captured in our model.

Figure 4: Cumulative default and survival rates, by credit score.





Source: Black Knight Financial Services, LPS McDash Data; and author calculations.
Note: Projections assume the LTV is 70.

3.3 Forecast Methodologies

When determining expected losses under CECL for a portfolio of loans, risk managers have to make many modeling assumptions. The choice of model, conditioning variables, estimation data, length of the forecast window, and the path of macroeconomic conditions all must be decided. In this paper, we focus on three broad categories of forecasts that, in a stylized way, capture the range of variation we might expect to see in projections by professional forecasters. The first is an optimistic forecast where, regardless of the current macroeconomic environment, forecasters continually anticipate steady month-over-month growth. We assume a constant 0.6 percent monthly change in home prices which is also our data sample's average county level growth rate during the analysis period.

For a forecast initiated at time t regarding a period $t + j$ in the future, the optimistic forecast $HP_i^{Optimistic}(t + j)$ is given by the following

$$HP_i^{Optimistic}(t + j) = (1 + .6)^j \times HP_i^{Observed}(t - 1)$$

where $HP_i^{Observed}(t - 1)$ is the actual, observed county home price as of time $t - 1$.

The second forecast represents a continuation of near-term macroeconomic trends modeled in an autoregressive (AR) fashion. In other words, a forecast that is optimistic during recoveries and pessimistic during downturns. By construction, an AR model is not likely to accurately predict inflection or turning points of macroeconomic factors. The AR model is estimated using a simple, autoregressive structure incorporating the last 1, 2, 3, 6, and 12 monthly lags along with fixed effects $\boldsymbol{\theta_i}$ for each local county. The regression is estimated on California's county level property prices from 1977 to 2016.

$$HP_i^{AR}(t+j) = \begin{cases} \beta_0 + \sum_{j=1}^{1,2,3,6,12} \beta_j \, HP_i^{Observed}(t-1) + \boldsymbol{\theta_i} \; if \; j = 0 \\ \beta_0 + \sum_{j=1}^{1,2,3,6,12} \beta_j \, HP_i^{AR}(t+j-1) + \boldsymbol{\theta_i} \; else \end{cases}$$

The third is a limited foresight model that assumes forecasters have a limited capacity to predict the future. These forecasts are accurate for 2 quarters after which they are followed by 6 quarters of a flat line forecast. Outside of our 2-year reasonable and supportable projection window, all forecasts revert back to the model that conditions only on factors at origination.

$$HP_i^{LF}(t+j) = \begin{cases} HP_i^{Observed}(t+j) \; if \; j < 24 \\ HP_i^{LF}(t+24) \; if \; j \geq 24 \end{cases}$$

We also consider the forecast update frequency by examining the ALLL that would be built under the three forecast methods that are updated at different frequencies. Sluggishness in the forecast updates gives us a proxy for measurement error in the real-time measurement of the economic conditions. The intuition, based on the findings in Oprhanides and van Norden (2002) is that banks develop economic forecasts in real-time, and the underlying series they are forecasting contain noise. When information is revised and the uncertainty cleared, risk managers have an opportunity to revise their expectations and determine the path of ALLL appropriately. In some cases when forecasts are revised at a period of economic weakness, the path of ALLL may sharply fluctuate to accommodate the revision. We examine scenario frequencies that are updated quarterly, semi-annually, annually, and bi-annually.[12] In the notation above, this would mean updating $HP_i^r(t+j)$ for every 3, 6, 12, 24 values for t.

[12] GAAP accounting rules require the forecasts to be updated at the frequency of financial reporting, which for many banks is at the quarterly level.

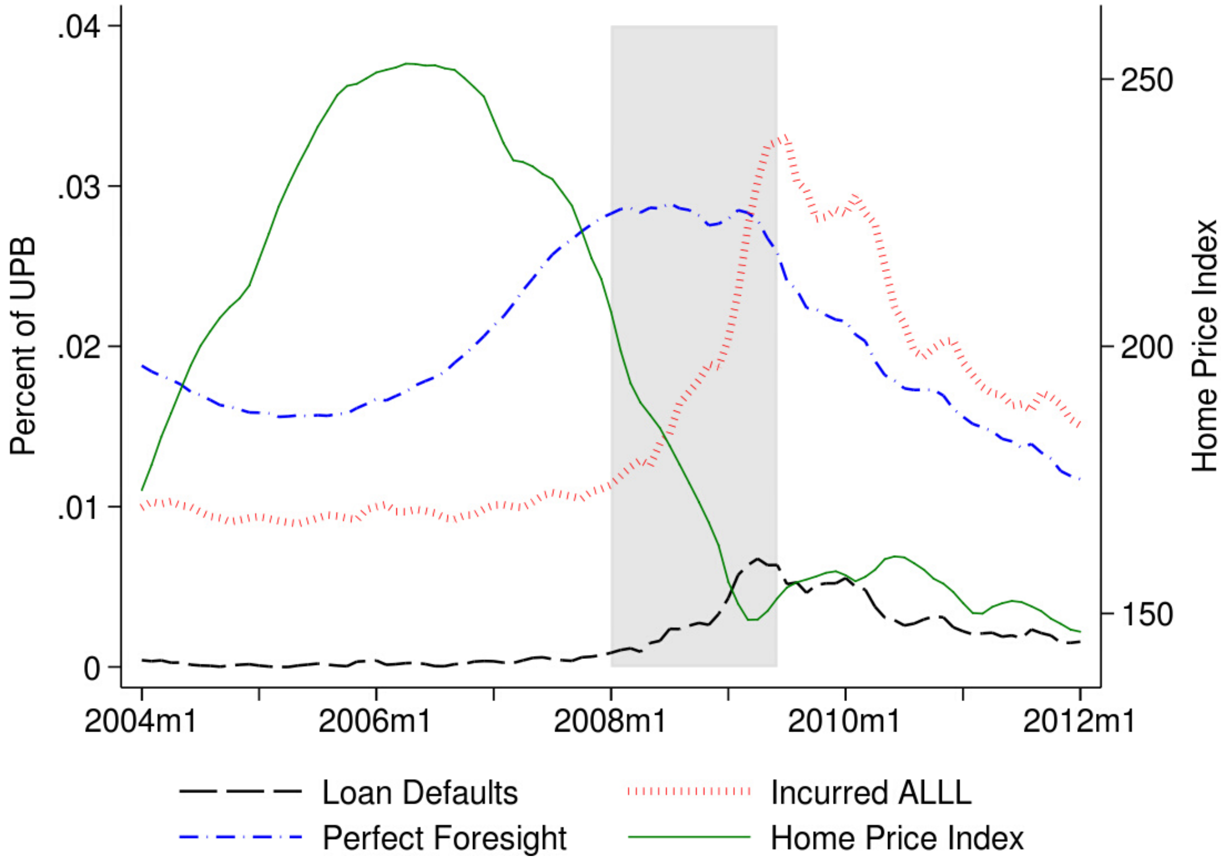
4. Results

4.1 Incurred Loss Standard and CECL with Perfect Foresight

Examining how ALLL behaves under the incurred loss standard versus CECL with perfect foresight of macroeconomic conditions can illustrate how CECL reduces pro-cyclicality. Figure 5 below shows ALLL under the incurred loss standard in dashed red along with the path of California's home price index in green. We construct ALLL under the incurred loss standard by extrapolating the relationship between defaults and ALLL in the Y-9C data from Figure 1 to the estimation sample.[13] The extrapolation preserves the dynamics of how ALLL would have responded to the rise in loan delinquencies.

[13] Because loan-level provisioning and ALLL data is not available for this sample of Californian mortgages from LPS McDash, we extrapolate what ALLL would have looked like for this sample of loans using aggregate provisioning data from the Y-9C.

Figure 5: ALLL under Incurred and CECL with Perfect Foresight



Source: Federal Reserve Board, Form FR Y-9C, Consolidated Financial Statements for Bank Holding Companies; Black Knight Financial Services, LPS McDash Data; and author calculations

Note: Incurred ALLL represents loan-level reserves interpolated from a model of bank's ALLL as a function of charge offs and loan defaults. CECL with perfect foresight of macroeconomic conditions shows ALLL under the expected loss model and conditions on the actual path of home prices in the following two years, afterwards reverting back to the long run experience.

ALLL under the incurred loss standard is relatively pro-cyclical, under-provisioned at the height of home prices initially and over-provisioned at the trough. As Californian home prices started to weaken in early 2006, ALLL does not smoothly increase in response, but instead is quickly increased in a somewhat volatile fashion only after home prices had bottomed out in 2009. There is little forward-looking behavior – banks increased provisioning charges at exactly the time when their revenues were under greatest stress. The peak of ALLL under the incurred loss standard occurs roughly 15 months after the start of the recession.

Contrast this behavior with how CECL given perfect foresight of macroeconomic conditions would behave. The blue line in figure 5 shows ALLL under CECL, calculated using the estimated model, with the forecast as the actual, observed home price

$$HP_i^{Perfect}(t+j) = HP_i^{Observed}(t+j)$$

Provisioning charges increase smoothly beginning in 2006 with the peak in ALLL reached at the beginning of the recession in 2008. Compared to the pattern of volatile provision charges exhibited under the incurred loss regime during 2008 and 2009, the ALLL under CECL with economic certainty is less pro-cyclical. ALLL peaks prior to a significant fall in home prices.

However, one advantage of the incurred loss regime is a relatively transparent relationship between provisioning and credit quality. Given that incurred loss is a backwards-looking measure, increases or decreases in the stock of ALLL can be interpreted as rises or falls in credit risk conditional on risk characteristics such as geographic concentration and credit scores. These relationships, particularly for retail lending, are well understood by market participants who can adjust their expectations of credit risk accordingly. Under CECL, increases in ALLL could also be due to changes in economic forecasts or assumptions that are orthogonal to changes in portfolio composition and risk drivers. When forecasts are perfect, ALLL is a forward-looking measure of economic trends reflecting underlying risk. But if forecasts contain idiosyncratic assumptions by risk managers, then comparability may be hindered across banks and time as additional subjectivity confounds the relationship between ALLL and risk.

4.2 Alternative Forecasting Methods

While CECL with perfect foresight provides forward-looking provisioning, in most cases banks will not be able to perfectly assess macroeconomic conditions. Instead, risk managers must condition on a specific forecast subject to modeling decisions. Here we examine the impact on ALLL from three different forecasts.

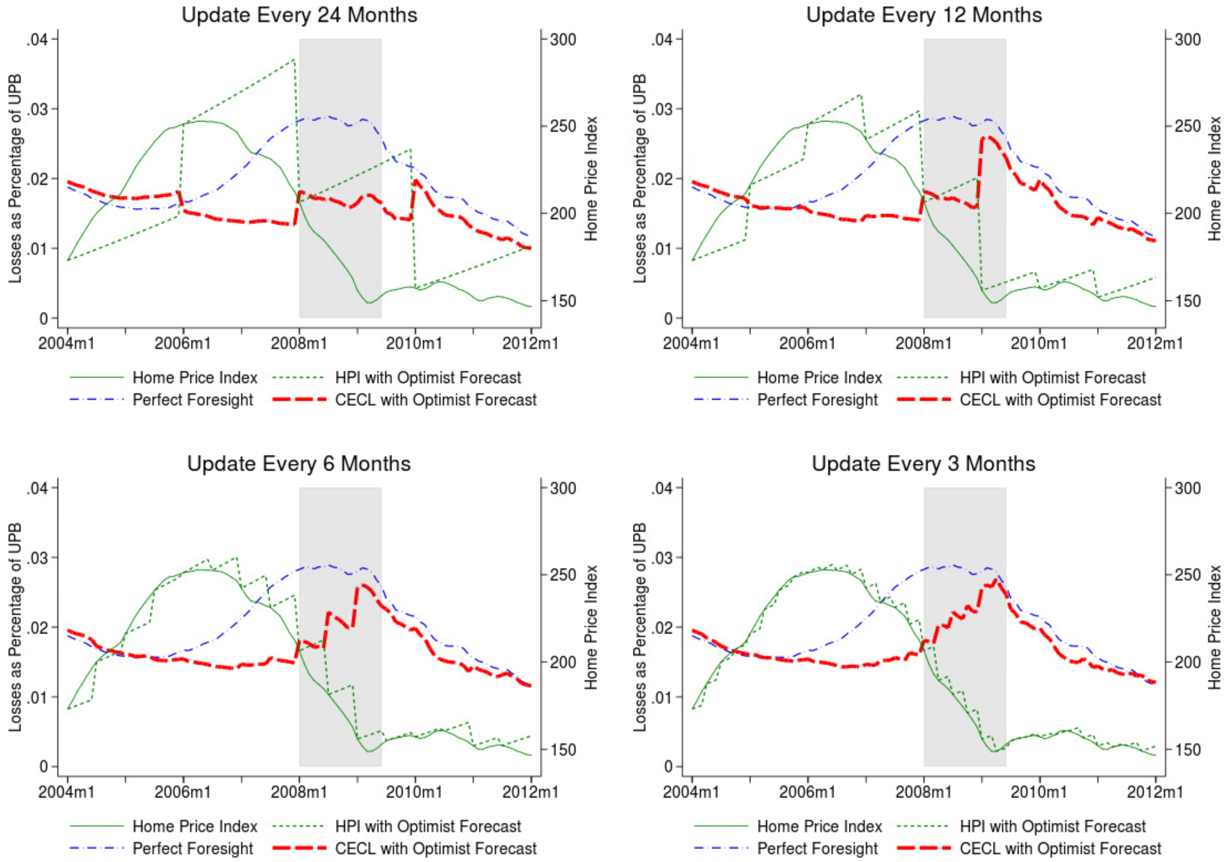
Figure 6 shows an optimistic forecast. Home prices are assumed to rise by 0.6 percent each month following California's average county level growth rate from 2002-2015. Plotted in dashed green, the forecast noticeably under-predicts home prices from 2004-2006 while over-predicting HPI after 2006. The orange line shows the path of ALLL under these forecasts given the expected loss model. Predictably, ALLL is below that of the level described by CECL with perfect foresight given the lower levels of expected LTV under an optimistic path.

Each panel in figure 6 also represents a different forecast update window. To increase precision, risk managers may decide to frequently update their forecasts given more recent information on the current environment. The timing of when these revisions occur is also likely to contribute to the volatility of expected losses. The intuition here is that these forecasts are developed with some noise about the true state of the economy. When the uncertainty is revealed later on given additional information, the risk manager revises his or her estimates and adjusts accordingly. This delay may also constrain higher frequency updates. Shown in figure 6 are update windows at the 24, 12, 6, and 3 month intervals.

With lower frequency updates, provisioning given an optimistic forecast is somewhat volatile as ALLL moves significantly following each revision. This is especially true in periods of large price movements where the stale forecast diverges from current conditions, the optimistic forecast is prone to adjustments that necessitate sharp changes in expected losses and ALLL. At higher frequencies, ALLL buildup is smoother.[14]

[14] Even at higher frequencies such as every 3 months, at any given point the forecasts will diverge from the actual path of home prices. The forecast lines are not extended in the panel for ease of illustration. This is why the path of ALLL under perfect foresight differs from the optimistic CECL even though the green and dashed lines appear similar.

Figure 6: Alternative Forecast – Optimistic

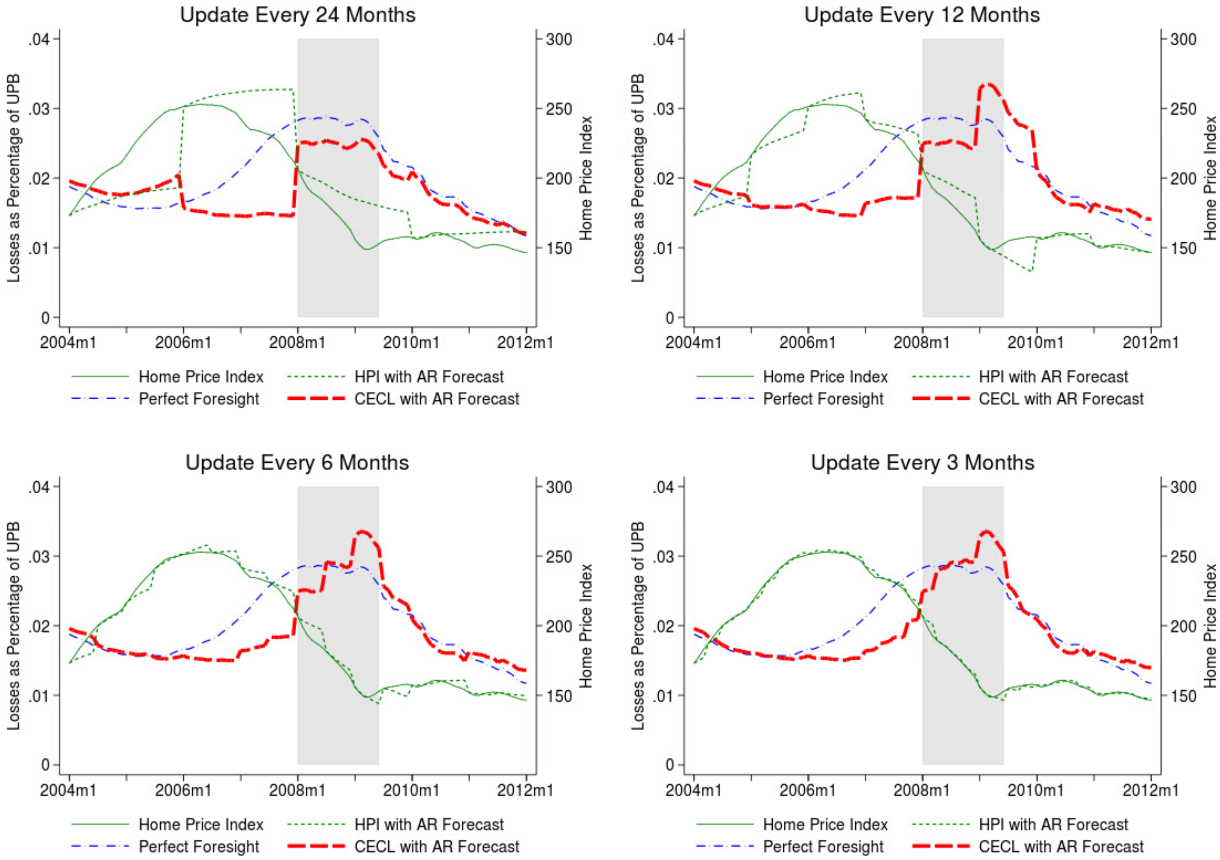


Source: Federal Reserve Board, Form FR Y-9C, Consolidated Financial Statements for Bank Holding Companies; Black Knight Financial Services, LPS McDash Data; and author calculations

Note: CECL with perfect foresight of macroeconomic conditions shows ALLL under the expected loss model and conditions on the actual path of home prices in the following two years, afterwards reverting back to the long run experience. The optimist forecast assumes a constant .6 percent monthly increase in the HPI index. Each panel allows the forecast to be updated at increasingly frequent intervals. Each of the HPI forecast lines is only graphically depicted in the period for which it is current – each of the underlying forecasts extends further.

ALLL under the optimistic forecast is also less forward-looking than CECL with perfect foresight – provisions are increased only after home prices have fallen significantly. This pattern is somewhat similar to ALLL under the incurred loss standard – both exhibit rapid buildup throughout 2008 and 2009 as home prices approach the bottom.

Figure 7: Alternative Forecast - Autoregressive



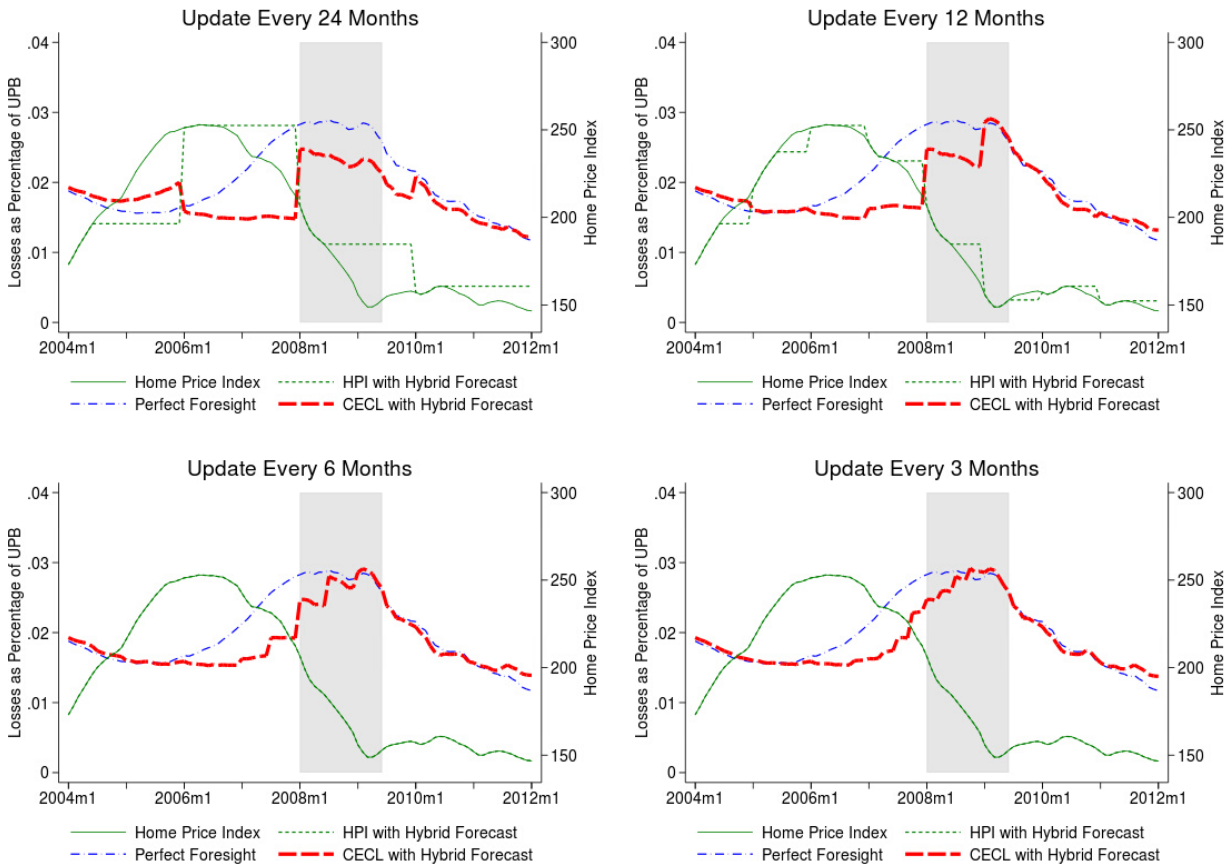
Source: Federal Reserve Board, Form FR Y-9C, Consolidated Financial Statements for Bank Holding Companies; Black Knight Financial Services, LPS McDash Data; and author calculations

Note: CECL with perfect foresight of macroeconomic conditions shows ALLL under the expected loss model and conditions on the actual path of home prices in the following two years, afterwards reverting back to the long run experience. The autoregressive forecast continues the recent price movements of the last 4 quarters. Each panel allows the forecast to be updated at increasingly frequent intervals. Each of the HPI forecast lines is only graphically depicted in the period for which it is current – each of the underlying forecasts extends further.

Next we examine a forecast that is designed to continue recent price movements into the future in an autoregressive specification. Again we plot this for 24, 12, 6, and 3 month update windows. Figure 7 shows that the AR technology leads to different patterns than the perfect foresight or optimistic forecasts. With an autoregressive forecast, near-term trends are assumed to continue so that downturns are worsened and recoveries are magnified. Almost mechanically, ALLL established under AR forecasts will generally miss inflection and turning points, resulting in somewhat pro-cyclical patterns.

Provisioning is below the level of ALLL under perfect foresight prior to 2007 as the AR specification forecasts continued home price growth, similar to the optimistic scenario. From 2007 to 2009, the two largely mirror each other as the AR model accurately fits the actual path of home prices. After 2009 however, there is a sudden increase as ALLL is forecast to be much higher due to the continued weakening of home price forecasts compared to the actual trough. The AR forecast is not able to forecast the inflection point of home prices which leads to large increases in ALLL in early 2009. Compared to the perfect foresight case, ALLL under an AR forecast is thus more pro-cyclical and less forward-looking.

Figure 8: Alternative Forecast – Hybrid

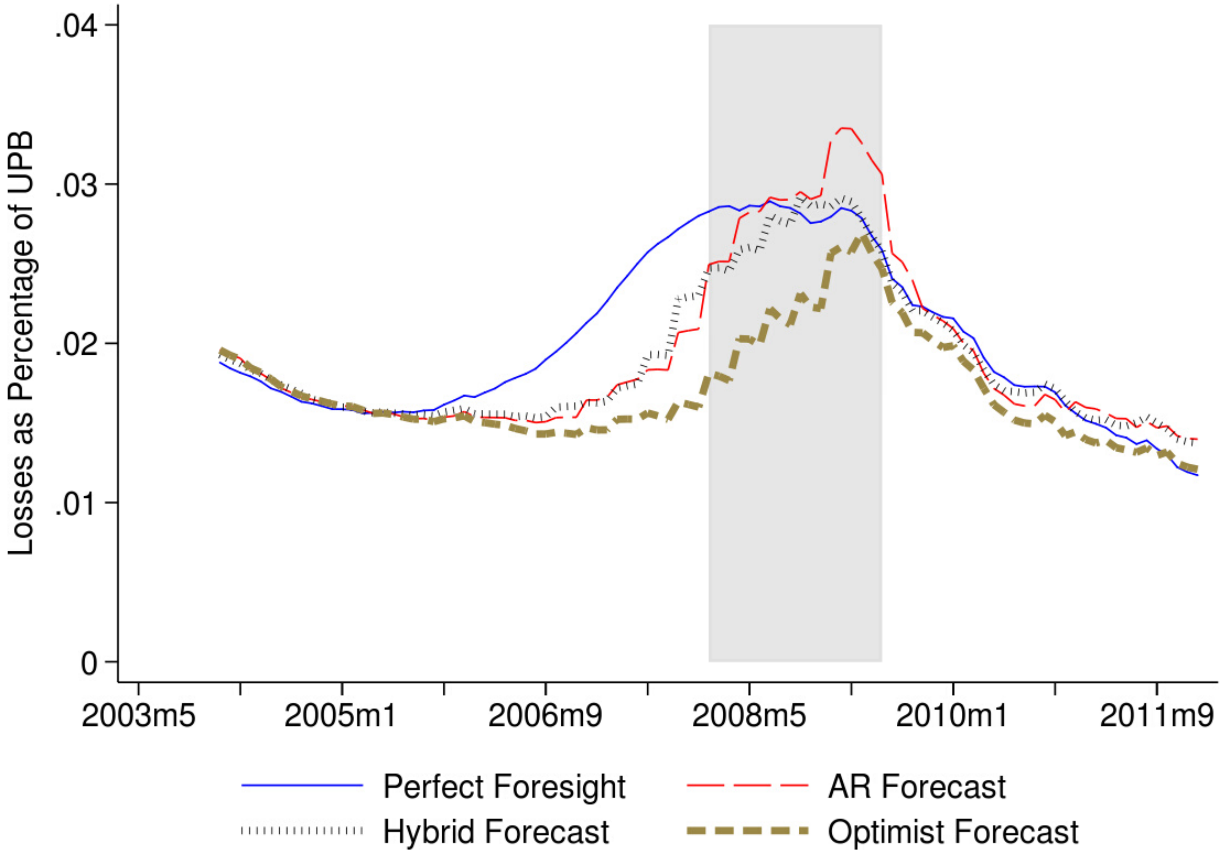


Source: Federal Reserve Board, Form FR Y-9C, Consolidated Financial Statements for Bank Holding Companies; Black Knight Financial Services, LPS McDash Data; and author calculations

Note: CECL with perfect foresight of macroeconomic conditions shows ALLL under the expected loss model and conditions on the actual path of home prices in the following two years, afterwards reverting back to the long run experience. The hybrid forecast tracks the actual macroeconomic conditions for 2 quarters and then reverts back to a flat forecast for the remaining 6 quarters. Each panel allows the forecast to be updated at increasingly frequent intervals. Each of the HPI forecast lines is only graphically depicted in the period for which it is current – each of the underlying forecasts extends further.

The last forecast represents a risk manager with a limited ability to predict the future. Forecasts are accurate for 2 quarters, after which the forecast reverts back to a flat line forecast. As shown in figure 8, the resulting ALLL approaches that of the perfect foresight forecast. ALLL is built earlier in the economic cycle and is less volatile than under the incurred loss standard or the alternative forecasts considered here. To the extent that risk managers have an ability to forecast the future, even for limited periods, it is likely to lead to a decrease in the degree of pro-cyclical provisioning.

Figure 9: Comparison of Alternative Forecasts Updated Every 3 Months



Source: Federal Reserve Board, Form FR Y-9C, Consolidated Financial Statements for Bank Holding Companies; Black Knight Financial Services, LPS McDash Data; and author calculations

Note: CECL with perfect foresight of macroeconomic conditions shows ALLL under the expected loss model and conditions on the actual path of home prices in the following two years, afterwards reverting back to the long run experience. The optimist forecast assumes a constant .6 percent monthly increase in the HPI index. The autoregressive forecast continues the recent price movements of the last 4 quarters. The hybrid forecast tracks the actual macroeconomic conditions for 2 quarters and then reverts back to a flat forecast for the remaining 6 quarters.

Figure 9 illustrates just how wide the range of ALLL is for different forecasts even given higher frequency updates. At the beginning of the recession in late 2007, the allowance under perfect foresight would have been nearly 1.5 percentage points higher than under the optimistic forecast, .9 percent higher than the autoregressive, and 0.5 percent higher than the hybrid. Compared to the dispersion in unemployment forecasts shown in figure 2, if home price forecasts show the same variability, then allowances are likely to vary even more. By introducing additional modeling decisions into the calculation of expected loan losses, the link between ALLL and portfolio risk is weakened. Given the same underlying portfolio, this may hinder comparability across banks, making it difficult for the market to disentangle portfolio risk from forecast uncertainty.

5. Conclusion

CECL is a major overhaul to loan loss provisioning from an incurred loss to a forward-looking standard. In this study, we develop a model of expected mortgage losses and demonstrate some stylized facts. First, to the extent that risk managers have a capacity, even somewhat limited, to predict near-future macroeconomic trends, CECL should achieve its goals and lead to a less pro-cyclical, more forward-looking provisioning behavior than the incurred loss standard. This should dampen the degree to which reserves are overstated at the trough of an economic cycle and understated at its peak.

Second, the introduction of an expected loss framework requires settling many modeling decisions. These decisions, the effects of which are likely to be opaque to market participants, may nonetheless have a material effect on loss predictions. We show the range of loss estimates due to one model decision: the choice of forecast. Results show that, controlling for portfolio composition, differences in the methodology used to construct forecasts and differences in the timing of revisions to those forecasts can have a nontrivial effect on loan loss provisions. These modeling decisions potentially hinder comparability across banks and time if markets are not able to disentangle the degree to which the variation in provisions is driven by credit risk versus model uncertainty.

References

Batchelor, R. A., & Dua, P. (1990). Product differentiation in the economic forecasting industry. International Journal of Forecasting, 6(3), 311-316.

Bernanke, B. S. and C. S. Lown (1991) "The Credit Crunch," Brookings Papers on Economic Activity 2, 205-247.

Berrospide, J. and R. Edge (2010) "The effects of bank capital on lending: What do we know, what does it mean?," International Journal of Central banking 6(4), 5-55.

Cohen, B. H. and G. A. Edwards, Jr. (2017) "The New Era of Expected Credit Loss Provisioning," BIS Quarterly Review, March, pp. 39-56.

Cornett, M., McNutt, J., Strahan, P., Tehranian, H. (2011) "Liquidity Risk Management and Credit Supply in the Financial Crisis," Journal of Financial Economics 101, 297-312

Carlson, M., H. Shan, M. Warusawitharana (2013) "Capital ratios and bank lending: A matched bank approach," Journal of Financial Intermediation 22, 663-687

Goodman, Laurie, J. Zhu (2015) "Loss Severity on Residential Mortgages", Urban Institute Housing Finance Policy Center Brief

International Accounting Standards Board (2013) "IFRS 9 Financial Instruments," July.

Kishan, R., and Opiela, T (2000) "Bank Size, Bank Capital, and the Bank Lending Channel," Journal of Money, Credit, and Banking 32, 121-141.

Financial Accounting Standards Board (2016) "Accounting Standards Update No. 2016-13, Financial Instruments—Credit Losses (Topic 326): Measurement of Credit Losses on Financial Instruments," June.

Francis, W.B. and M. Osborne (2009) "Bank Regulation, capital and credit supply: measuring the impact prudential standards," Occasional Paper 36, Financial Services Authority.

Orphanides, A., & Van Norden, S. (2002). The unreliability of output-gap estimates in real time. The Review of Economics and Statistics, *84*(4), 569-583.

Peek, J. and E. S. Rosengren (1995) “The Capital Crunch: Neither a Borrower nor a Lender Be,” Journal of Money, Credit, and Banking, 27, 625–638.

Appendix A: Hazard Model Estimates

	Origination Model		Refreshed Model	
	Prepay	Default	Prepay	Default
Credit Score				
600 to 619	0.0415	-0.14	0.0633	-0.17
	(0.09)	(0.17)	(0.09)	(0.17)
620 to 639	-0.0905	-0.133	-0.0844	-0.0899
	(0.07)	(0.14)	(0.07)	(0.14)
640 to 659	-0.109	-0.297**	-0.0842	-0.324**
	(0.07)	(0.13)	(0.07)	(0.13)
660 to 679	-0.110*	-0.593***	-0.0907	-0.529***
	(0.07)	(0.13)	(0.07)	(0.13)
680 to 699	-0.115*	-0.755***	-0.0937	-0.707***
	(0.07)	(0.13)	(0.07)	(0.13)
700 to 719	-0.0965	-0.972***	-0.0855	-0.817***
	(0.06)	(0.13)	(0.06)	(0.13)
720 to 739	-0.0834	-1.154***	-0.0763	-0.982***
	(0.06)	(0.13)	(0.06)	(0.13)
740 to 759	-0.056	-1.535***	-0.06	-1.257***
	(0.06)	(0.13)	(0.06)	(0.13)
760 to 779	0.00516	-1.950***	-0.00783	-1.589***
	(0.06)	(0.14)	(0.06)	(0.14)
780 to 799	0.0413	-2.468***	0.0266	-2.055***
	(0.06)	(0.15)	(0.06)	(0.15)
800+	-0.0584	-2.754***	-0.0809	-2.212***
	(0.06)	(0.18)	(0.06)	(0.18)
LTV				
20 to 29	0.0211	1.001	-0.0730*	-0.686
	(0.06)	(0.61)	(0.04)	(0.49)
30 to 39	0.111**	0.972	0.0714*	0.0731
	(0.06)	(0.60)	(0.04)	(0.39)
40 to 49	0.136**	1.423**	0.187***	0.308
	(0.05)	(0.59)	(0.04)	(0.38)
50 to 59	0.188***	1.915***	0.255***	0.718*
	(0.05)	(0.58)	(0.04)	(0.37)
60 to 69	0.191***	2.297***	0.335***	1.264***
	(0.05)	(0.58)	(0.04)	(0.36)
70 to 79	0.229***	2.539***	0.225***	1.828***
	(0.05)	(0.58)	(0.04)	(0.36)
80 to 89	0.176***	2.695***	-0.126***	2.424***
	(0.05)	(0.58)	(0.04)	(0.36)
90 to 99	0.158***	2.609***	-0.311***	2.971***

	(0.06)	(0.58)	(0.05)	(0.36)
100 to 109	-0.141*	2.012***	-0.459***	3.382***
	(0.08)	(0.61)	(0.06)	(0.36)
110 to 119	-0.624***	2.143***	-0.545***	3.612***
	(0.13)	(0.65)	(0.07)	(0.36)
120+	-0.783***	1.833***	-0.529***	3.860***
	(0.12)	(0.65)	(0.06)	(0.36)
Constant	-24.22	-27.02	-23.95	-26.2
	-782.5	-2057	-685.6	-1578
Pseudo R-squared	0.0216		0.0337	
Periods at Risk	1780791		1780791	