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The Effect 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*

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Abstract

CECL, the new credit loss provisioning standard, is intended to promote proactive provisioning as loan loss reserves must incorporate forward-looking assumptions. We study how one assumption – expectations about future house prices – affects the size and timing of provisions for residential mortgage portfolios. While provisions under CECL are generally less pro-cyclical compared to the incurred loss standard under various forecasts and measures of pro-cyclicality, 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 idiosyncratic differences in forecasting methods.

JEL codes: G21, G28, M41, M44

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

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1. Introduction

Accounting standards are a set of financial reporting standards established to provide information to investors and market participants. Recently, the Financial Accounting Standards Board (FASB) developed CECL – a new standard for provisioning allowances for loan and lease losses (ALLL) – to address the problem that loan provisions were "too little, too late" (i.e., pro-cyclical) during the past financial crisis.[1] While incorporating assumptions about the future may reduce pro-cyclicality, idiosyncratic differences in modeling assumptions could also complicate the comparison of provisions by investors and market participants. Therefore, studying the impact of different modeling assumptions on the size and timing of provisions is critical for understanding whether CECL can achieve both its macro-prudential and financial reporting goals.

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 that 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 a downturn when economic conditions have begun to deteriorate but losses have not. Delayed recognition of losses earlier in the cycle can result in significant, rapid, and volatile increases in provisions (with corresponding reductions in regulatory capital) in the midst of a downturn. That is, the current 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.[2] Under CECL, when a bank originates a loan, the total expected credit losses over the entire contractual life of the exposure are recognized. CECL requires a forward-looking approach. Under that approach, banks must provision for losses under future conditions – a practice prohibited under incurred loss – so that ALLL are increased earlier in the economic cycle. As a result, provisions under CECL should be

[1] In the United States, the FASB is responsible for maintaining the U.S. Generally Accepted Accounting Principles (U.S. GAAP) that govern accounting standards. The FASB issued its revised ALLL standard as CECL in June 2016 (FASB 2016).

[2] This paper will abstract from the various other considerations on ALLL that have been well-documented by the literature that can also lead to low ALLL. Bank managers have incentives to fluctuate loan loss provisions for earnings management and capital management purposes. In particular, Cohen et al. (2014) show that banks demonstrating more aggressive earnings management prior to 2007 exhibit substantially higher stock market risk at the onset of the financial crisis. See Beatty and Liao (2014) for a review of the related empirical work.

larger when entering a downturn and less pro-cyclical. The exact magnitude of the increase depends on the quality of the forecast and modeling assumptions used.

However, determining expected losses requires risk managers to make subjective assumptions about future conditions. Among those assumptions, risk managers will have to set expectations regarding future economic conditions that affect loan losses. Some in the banking industry assert that CECL would have been highly pro-cyclical had it been in place during the past crisis because macroeconomic models are generally unable to accurately predict turning points in the business cycle (Covas and Nelson 2018). 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, under a variety of different forecasts and definitions of pro-cyclicality, generally achieves its goal of being less pro-cyclical than the incurred loss standard: reserves peak before the trough of the cycle. However, the degree of pro-cyclicality can vary significantly for seemingly small differences in assumptions about future house prices. The variation of ALLL through the business cycle has important implications on bank earnings and directly affects bank capital, which in turn influences the availability of credit to the economy. Specifically, there is an extensive literature on bank capital and lending that suggests that if ALLL could be less pro-cyclical, banks would have additional capital to support lending during a financial downturn.[3]

Given the recency of the accounting change, researchers are just beginning to explore the pro-cyclicality of CECL. Cohen and Edwards (2017) use a stylized top-down approach that demonstrates banks, with some capacity of foresight, could have shifted provisions before the crisis. In contrast, Abad and Suarez (2018) and Krüger et al. (2018) use bottom-up approaches and focus on business credit risk. More specifically, Abad and Suarez (2018) develop a ratings-migration model and find that a sudden unanticipated recession can lead to more severe provisioning under CECL than the incurred loss standard. In an extension, they also analyze situations where banks can anticipate changes in the economy one year out. Similar to our findings, the provisions are less severe with some foresight. Krüger et al. (2018) focus on the capital effects and conclude that CECL increases the pro-cyclicality of capital requirements.

[3] See for example, Bernanke et al. (1991); Berrospide and Edge (2010); Carlson et al. (2013); Cornett et al. (2011); Francis and Osborne (2009); and Kishan and Opiela (2000).

The distribution of forecast and modeling assumptions could also complicate the comparability of provisions across banks and time. Market participants such as investors and analysts rely on reported provisions, ALLL, and related disclosures to assess underlying portfolio risk. CECL requires institutions to disclose their accounting policies and methodology related to their reasonable and supportable forecasts, and it further requires institutions to discuss how these forecasts influenced management's expected credit losses. However, CECL does not require institutions to disclose quantitative details of individual forecast and modeling assumptions to allow users to analyze how these assumptions compare across banks. Under the incurred loss standard, as forecasting is prohibited, higher provisioning levels generally correspond directly to increased losses.

The number of modeling decisions required by CECL[4] – which may differ across banks or even across time for a given bank – may result in a deterioration of the historically tight link between ALLL and actual losses. For example, it is possible that similar levels of allowance could be established for higher risk portfolios with optimistic expectations as for lower risk portfolios with more conservative expectations. As a result, 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.[5]

Section 2 provides more background on the accounting for loan losses and what has changed with the new accounting standard. We present our empirical framework in Section 3, and discuss our results in Section 4. Section 5 concludes.

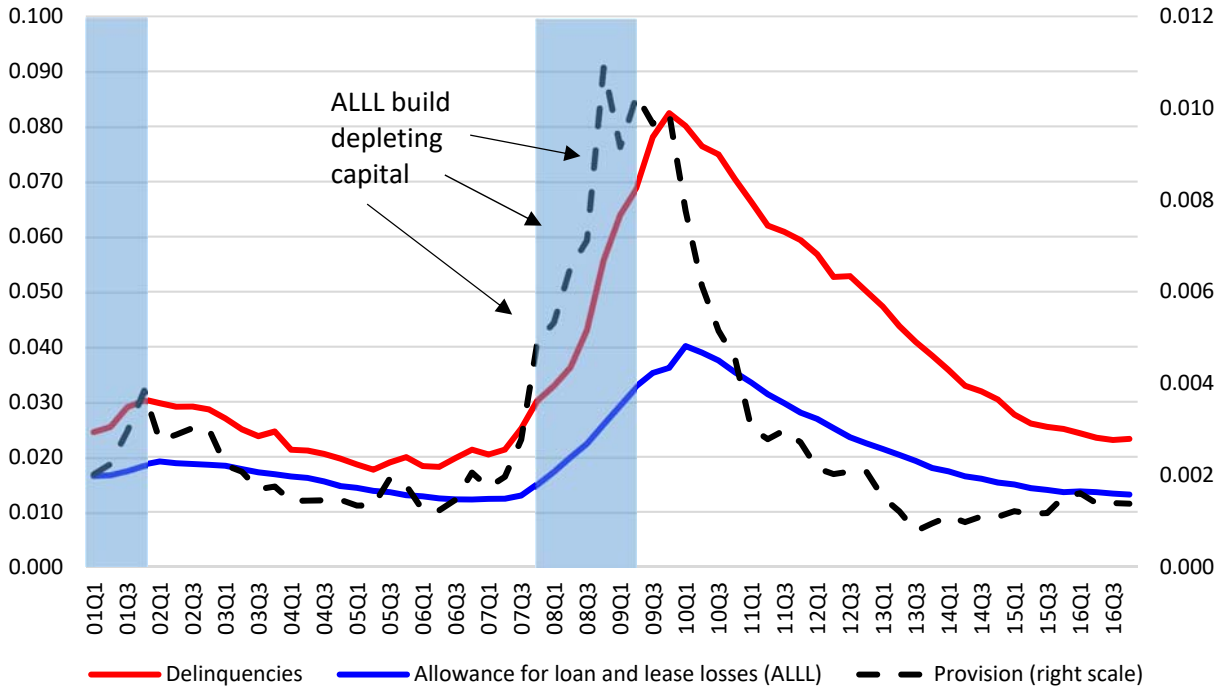
2. Overview of the Current Expected Credit Loss Standard (CECL)

Figure 1 highlights the problem of "too little, too late" by showing what happened to primary measures of total loan losses at bank holding companies (BHCs) between 2001 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

[4] For example, decisions include the determination of contractual lifetime for products without defined contractual end date and the approach to reversion.
[5] Byard et al. (2010) examined the impact of accounting disclosures and find that the link between financial reporting and information revelation is positively affected by stronger enforcement regimes and firm-level reporting incentives.

of the recession. During this period, bank capital continued to be stressed by the elevated provisioning.

Figure 1: Delinquencies, ALLL, and Provisions as a Percent of Total Assets, Bank Holding Companies, 2001-2016



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 recession periods 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 to address this issue of "too little too late."[6] In response, both the FASB and the International Accounting Standards Board (IASB) issued new expected credit losses standards.[7] In July 2014, the IASB issued IFRS 9, IASB's new expected credit losses standard, and in June 2016, the FASB issued CECL.[8] CECL and the IFRS 9 differ along several dimensions. Most notably, IFRS 9 is a staged approach in that only a

[6] 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)
[7] Refer to the FASB's June 6, 2016 news release (link) and IASB's project summary (link) for additional background information.
[8] For most institutions applying IFRS 9, the standard is effective in 2018 (IFRS 2014). For institutions applying CECL, the standard is effective in 2020 for SEC filers and 2021 for non-SEC filers (FASB 2016).

portion of the overall loan portfolio with a significant increase in credit risk is required to hold lifetime expected credit losses (generally, performing assets are required to carry only 12 months of expected credit losses), whereas CECL requires lifetime expected credit losses to be held for all loans.

While both the IFRS 9 and CECL approaches allow banks to use forward looking information with the goal of building reserves sooner in the economic cycle, this outcome is not guaranteed. In particular, if forecasters have limited ability to predict inflection points of the economy, estimation of the appropriate level of ALLL may still be too low entering a recession. Additionally, sudden downward revisions in economic forecasts at the beginning of a recession could produce volatile increases in provisions, which could also increase pro-cyclicality. Given these possibilities, the degree to which CECL is more forward-looking is largely an empirical question. This paper attempts to address this question using a loan-level loss model, a variety of forecasts, and alternative measures of pro-cyclicality.

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 BHCs are comprised of HFI loans and HTM securities (2016:Q4). In this paper, we model the treatment of CECL for the loan book, specifically residential mortgages.

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 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).[9] Reverting back to a historical relationship can be immediate or over a period of time to reflect the contractual term of the financial asset.

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 method for measuring expected credit losses and allows financial institutions to choose methods that reasonably reflect 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 market participants with information about the riskiness of the loans held by the banks and about banks' ability to absorb loan losses. There is also a long literature using loan loss provisions to understand risk. Beginning with Beaver et al. (1989) researchers have documented the relationship between equity market value and ALLL. Beatty and Liao (2014) provide a review of the literature, explaining that the relationship between ALLL and market value can be supported with signaling arguments.

However, CECL introduces a number of new sources of variation in the calculation of ALLL that may cloud that information and make comparisons across banks and time more difficult. This is in contrast to SEC guidance in 2001 that improved the information content of ALLL for banks with strong earnings or capital (Beck and Narayanamoorthy 2013).

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.

[9] The relevant language in the FASB Accounting Standards Update No. 2016-13 is the following: "However, an entity is not required to develop forecasts over the contractual term of the financial asset or 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 320-20-30-8 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."

Other 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*.[10] That 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 confounding factor into the relationship between portfolio risk and changes in ALLL. It is that source of variation, requiring subjective, bank-specific idiosyncratic forecasting choices that is the subject of this paper. Note that this is separate from general model uncertainty or data risk. The empirical analysis considered here will be using the exact same credit loss model and input data – only the forecast of future conditions will change. Variation in credit loss models, calibrated to different data, could create even more variation in ALLL across the banking industry.

2.3 Uncertainty in Macroeconomic Forecasts

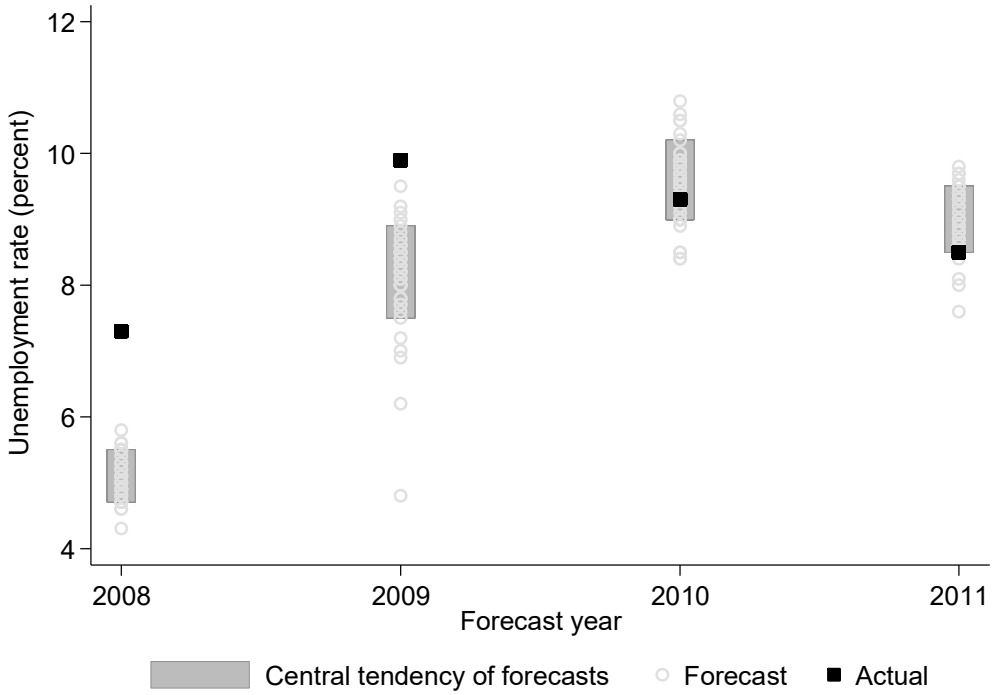
There are many challenges associated with forecasting that contribute to disagreement among macroeconomic forecasts. Some challenges are related to changes in the structure of the macroeconomic environment; others derive from issues associated with the real-time measurement of the data that are the inputs of the forecasts.[11] Others, still, are driven by forecaster biases that may be behavioral or rational (see Batchelor and Dua 1990).

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 generally be less pro-cyclical, the *degree* of pro-cyclicality depends on forecast quality and modeling assumptions.

[10] Although certain accounting standards already require incorporation of forward-looking information in accounting estimates, there are significant new judgments introduced by CECL. For example, the concept of *reasonable and supportable* forecasting period and the requirement to revert to unadjusted historical loss information are new and significant accounting requirements under CECL.

[11] 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.

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 credit-risk idiosyncrasies, we restrict our empirical investigation to first-lien residential mortgages. We focus on mortgages with a tailored loan-level model instead of a broader portfolio snapshot 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, which may be the case with using aggregated models across different loan categories. Additionally, first-lien mortgages are a large share of portfolio loans (about 20 percent of BHC loans) and many have long contractual lives (30 years), making them an important asset class to analyze.

We estimate a mortgage default and prepayment model that conditions loan-level losses on the future 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 forecasts of home prices. We start our analysis with a simple demonstration of motivation behind CECL. 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. 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," and other measures related to the timing and severity of provisioning. In other words, the peak of ALLL under CECL occurs before the peak of ALLL under the incurred loss method.

Because the actual path of home prices is not known, we continue our analysis by seeding our model with counterfactual home prices reflecting different forecasts about the future. While risk managers must make assumptions along hundreds of modeling dimensions, in this paper we focus on three broad types of forecasting methods: optimistic, continuation of recent trends (autoregressive), and a limited foresight assumption. Each method affects expected losses and the degree of pro-cyclicality differently, reflecting the variation in ALLL that may arise from different modeling assumptions. Our empirical analysis further establishes that even under imperfect forecasts, ALLL under CECL is generally less pro-cyclical than the incurred under various measures of pro-cyclicality.

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 2002 and 2015 and held as portfolio loans on bank balance sheets. California is the nation's largest housing market and the state experienced a statewide house price index (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 losses. The data contains 47,517 mortgages of which 30,099 (63 percent) prepay and 2,690 (5.7 percent) end in loan default. The remaining loans are still

current as of the last reported date of December 2015.[12] As a robustness check, we also repeat our analysis for Texas and Michigan, two other important mortgage markets which had somewhat different house price paths than California during the financial crisis.

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 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, which allows us to more easily work with alternative counterfactual home price forecasts. Additionally, by restricting our analysis to a relatively homogenous geographic sample of mortgages, our model should 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.[13] 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, loan 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 loan of surviving t periods without default or prepayment is given by

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

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 $\prod_{i=1}^{N} PD_i(t)$ for each loan $i = 1,2,\dots,N$.

We parameterize the default and prepayment hazard functions into two components: a baseline hazard that accounts for temporal seasoning effects as well as a hazard modeling loan-level risk drivers. We specify the baseline hazard using fixed effects for each payment month up to 120

[12] Note that the model parameters are specified using the entire sample period. In essence, the model has "learned" from the financial crisis. This again focuses the analysis on changes driven by forecast assumptions as opposed to model risk or behavioral bias (e.g., believing that very large house price corrections are not possible).

[13] Examples of other papers that have used hazard models to estimate mortgage default are Clapp et al. (2001); Clapp et al. (2006); de Servigny and Jobst (2007); Demyanyk and Van Hemert (2011); Deng and Gabriel (2006); Deng et al. (2000); Foote et al. (2008); and Tracy and Wright (2012)

(10 years). This allows each payment month to have its own payment and default rate, thereby providing a flexible treatment of repayment patterns across time.

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

The loan-level hazards $f_i^D(\cdot)$ and $f_i^P(\cdot)$ are further 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® Score 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 the implicit option to put the collateral back to the bank in exchange for extinguishing the loan (LTVs above 100).

We estimate two separate LTV hazards: one that uses 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 estimates of the hazard regressions.

We also include several other loan characteristics that have been found in the literature to be predictive of mortgage default or prepayment. Those include the original loan amount, dummy variables indicating that the loan was originated to refinance an existing mortgage (separate dummies for "cash-out" and "non-cash-out" refinances), and dummies indicating whether the mortgage was underwritten with partial or unknown amounts of documentation. Dummy variables also include the cumulative monthly payment increase and decrease to capture the effect of changes in payment size on the default and prepayment hazards.[14]

[14] Several studies have found that changes in payment size can affect default and prepayment hazards. Those include Tracy and Wright (2012), Johnson and Sarama (2015), and Epouhe and Hall (2016). The parameterization in our model is similar to that in Tracy and Wright, who study the effect of payment changes on first-lien mortgages.

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

$$H_i^j(LTV, FICO, X_{i,t}) = \begin{cases} H_i^{j,r}\left(\frac{UPB_{i,t}^R}{HP_i(t)}, FICO_i^o, X_i\right) \text{ if } LTV = \text{ Refreshed } LTV \\ H_i^{j,o}\left(\frac{UPB_i^{Orig}}{HP_i^o(t = Orig\ t)}, FICO_i^o, X_i\right) \text{ if } LTV = \text{ Orig. } LTV \end{cases} \text{ for } j = D, P \quad (3)$$

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 $FICO_i^o$ is the borrower's FICO® 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*, and X_i represents the additional loan characteristics included in the model. For our counterfactual analysis, the only difference across specifications is how we vary the forecast of $HP_i(t)$.

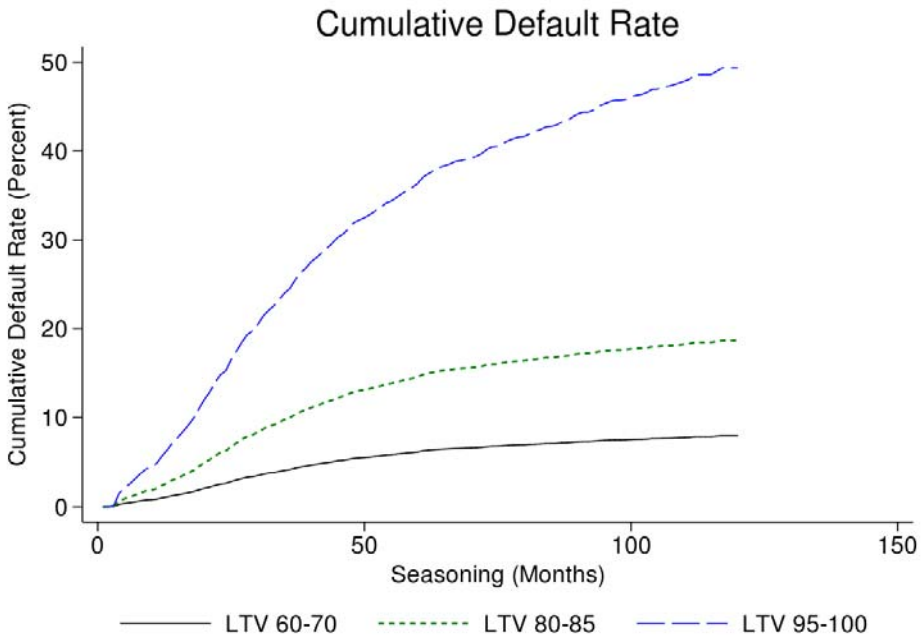
Incorporating both the origination and refreshed LTV is motivated by the CECL model's loss forecast period. Guidance indicates that banks should attempt to base their loss estimates on a "reasonable and supportable" forecast period. Outside of this period, loss estimates should revert back to the historical experience. We interpret this guidance by forecasting expected loan losses using the current, refreshed LTV for a two year period and then immediately 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.

$$CDR_{i,lifetime} = \sum_{t=1}^{24} H_i^{D,r}(t) + \sum_{t=25}^{120} H_i^{D,o}(t) \quad (4)$$

The predicted cumulative default rates $CDR_{i,lifetime}$ are then combined with a constant loss given default (LGD) assumption of 0.455 to arrive at an expected loss rate $E[Losses_{i,t}] =$

$0.455 * CDR_{i,lifetime} * UPB_{i,t}$.[15] Aggregated across all mortgages in our sample, the level of ALLL is calculated as the sum from the expected losses on current mortgages plus losses on the defaulted balances.

Figure 3: Cumulative Default Rate by Refreshed LTV.

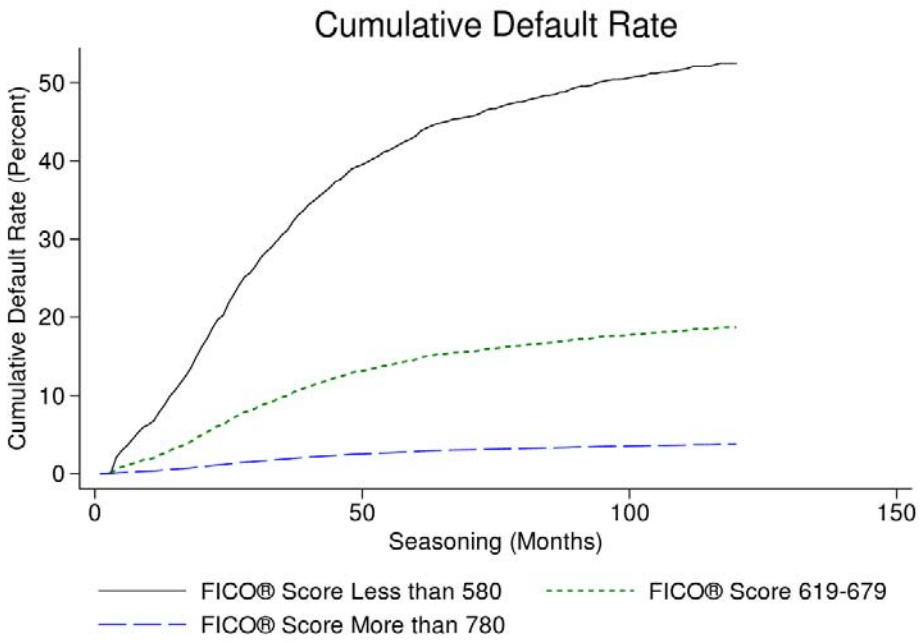


Source: Equifax Credit Risk Insight Servicing and Black Knight McDash Data and author calculations.
Note: CDR is calculated from the point-in-time model using the refreshed LTV score. Projections condition on an origination FICO® Score of 680-699.

Variation in the modeled default and survival rates across LTV and FICO® 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. Similarly, FICO® Scores between 780 and 799 rarely default, while scores between 600 and 620 have a default rate of about 20 percent after 5 years.

[15] Constant LGD makes the model less pro-cyclical. Goodman and Zhu (2015) find that the average loss severity for mortgages was 42.0 percent over the period 1999–2013 and 45.5 for California. However, pre- and post-crisis (1999-2004, 2009-2010) losses were 30.0 percent and 32.1 percent respectively. Losses from 2005 through 2008 were 44.0, 48.9, 47.6, and 43.3 percent respectively.

Figure 4: Cumulative Default Rate by FICO® Score.



Source: Equifax Credit Risk Insight Servicing and Black Knight McDash Data and author calculations.
Note: CDR is calculated from the point-in-time model using the refreshed FICO® Score. Projections condition on a refreshed LTV of 80-89.

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 categories of forecasts that, in a stylized way, capture some of 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 house price growth. We assume a constant 0.6 percent monthly change which is also the average county level growth rate for California during this period.

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

$$HP_i^{Optimistic}(t+j;t) = (1+0.6)^j \times HP_i^{Observed}(t-1)\ if\ j \geq 0 \tag{5}$$

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

The second forecast represents a continuation of near-term macroeconomic trends modeled in an autoregressive (AR) fashion. In other words, a forecast that is excessively optimistic during recoveries and overly 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.

$$HP_i^{AR}(t+j;t) = \begin{cases} HP_i^{Observed}(t+j)\ if\ j \leq 0 \\ \sum_{k=1}^{1,2,3,6,12} \widehat{\beta_k}\, HP_i^{AR}(t+j-k;t) + \boldsymbol{\theta_i}\ if\ j > 0 \end{cases} \tag{6}$$

The third is a limited foresight model that assumes forecasters have a limited capacity to predict the future. These forecasts are accurate for 6 months after which they are followed by a flat forecast of home prices.

$$HP_i^{LF}(t+j;t) = \begin{cases} HP_i^{Observed}(t+j)\ if\ j \leq 6 \\ HP_i^{LF}(t+6;t)\ if\ j > 6 \end{cases} \tag{7}$$

Note that outside of the reasonable and supportable projection window, the loan-level hazard immediately reverts back to the model that conditions only on factors as of origination. Reverting to the historical experience after the reasonable and supportable window constrains the possibility that low-quality forecasts diverge excessively from historical trends.

We also consider the forecast revision frequency by allowing the "jump-off" date of the three forecast methods to be updated at different frequencies. Sluggishness in forecast revisions gives us a proxy for measurement error in the real-time measurement of the economic conditions. The

intuition, based on the findings in Orphanides and van Norden (2002), is that banks develop economic forecasts in real-time and that the underlying data may 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. High-frequency revisions anchor the forecasts to current conditions as the economic cycle evolves.

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.[16] In the notation above, this would mean updating $HP_i^{Forecast}(t+j;t)$ for every 3, 6, 12, and 24 values for j.

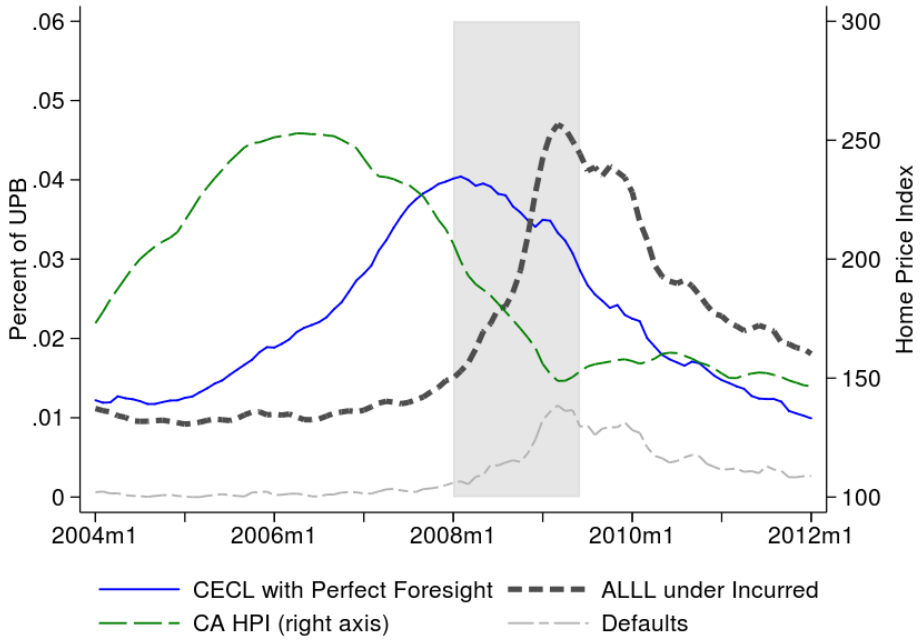
4. Results

4.1 Incurred Loss Standard and CECL with Perfect Foresight

The first comparison is examining ALLL under the incurred loss standard versus a benchmark of CECL with perfect foresight. Figure 5 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 for banks that have large mortgages exposures, defined as banks that have greater than 30 percent of their loan portfolio in first-lien mortgages. Because the relationship between ALLL and defaults in the Y-9C data is extrapolated across all portfolios, it is likely that the actual level of ALLL may differ from the first-lien data up to a scalar. However, the timing and build-up between ALLL and defaults is representative of provisioning under the incurred loss standard. Please see Appendix B for additional detail.

[16] GAAP accounting rules require the forecasts to be updated at the frequency of financial reporting, which for many banks is at the quarterly level. We added longer frequencies as institutions apply varying degrees of procedural rigor between annual and quarterly forecasting processes.

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; Equifax Credit Risk Insight Servicing and Black Knight McDash Data; and author calculations

Note: Mortgage defaults are defined as if the mortgage is 90+ days delinquent, in foreclosure, involuntary liquidation, or REO. ALLL under incurred represents loan-level reserves interpolated using Y-9C data from bank's ALLL as a function of charge offs and loan defaults. CECL with perfect foresight of macroeconomic conditions shows ALLL under the estimated expected loss model. The model 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 home prices started to weaken in early 2006, ALLL does not smoothly increase in response, but instead is flat through 2007 and is quickly increased in a somewhat volatile fashion only after home prices had fallen significantly by 2009. There is little forward-looking behavior – banks increased provisioning at exactly the time when their revenues and funding sources 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 with perfect foresight of macroeconomic conditions behaves. The blue line in figure 5 shows ALLL under CECL, calculated using the estimated model with the actual home prices used as the forecast

$$HP_i^{Perfect}(t+j) = HP_i^{Observed}(t+j) \tag{8}$$

Table 1 shows different measures of pro-cyclicality for incurred loss, CECL with perfect foresight, and CECL under alternative forecasts that are presented in the next subsection. CECL with perfect foresight (column 2) is less correlated with HPI and net charge-offs, has decreased volatility, and builds up reserves earlier than under incurred (column 1). Provisioning charges increase smoothly beginning in 2006 with the peak in ALLL reached at the beginning of the recession in 2008Q1 and prior to a significant fall in home prices. After 2008Q1 and during the crisis-period, ALLL under CECL is decreasing reflecting an earlier buildup compared to an increase of 3.01 percentage points under incurred. Compared to the pattern of volatile provision charges exhibited under the incurred loss regime during 2008 and 2009, ALLL under CECL with forecast certainty is less pro-cyclical.

Table 1: Measures of Pro-cyclicality (2004 – 2012)

Outcome	Incurred	Perfect Foresight	Optimistic	AR	Limited Foresight
Correlation with HPI	-76.1%	11.2%	-8.7%	-18.3%	-10.2%
Correlation with NCO	99.3%	25.1%	57.3%	55.5%	46.7%
Std Deviation of Provisions	5.3.E-03	2.2.E-03	3.1.E-03	3.1.E-03	2.5.E-03
Quarter of Largest % Decline	2010q1	2011q4	2009q3	2009q3	2009q2
Quarter of Largest % Increase	2008q4	2006q4	2009q1	2008q1	2007q4
Quarter of Peak ALLL	2009q1	2008q1	2009q1	2009q1	2008q4
Quarter of 90% Peak ALLL	2009q1	2007q3	2009q1	2008q2	2007q4
ALLL from 2006Q1 to Peak	3.65%	2.01%	1.30%	2.24%	1.75%
ALLL from 2006Q1 to 2008Q1	0.64%	2.01%	0.63%	1.69%	1.58%
ALLL from 2008Q1 to 2009Q1	3.01%	-0.67%	0.67%	0.55%	0.02%
Percent Increase post 2008Q1	82%	-33%	51%	25%	1%

Source: Federal Reserve Board, Form FR Y-9C, Consolidated Financial Statements for Bank Holding Companies; Equifax Credit Risk Insight Servicing and Black Knight McDash Data; and author calculations

Note: CECL with perfect foresight of macroeconomic conditions shows ALLL under the estimated expected loss model. The model conditions on the actual path of home prices in the following two years, afterwards reverting back to the long run experience. ALLL under incurred represents loan-level reserves interpolated using Y-9C data from bank's ALLL as a function of charge offs and loan defaults. The optimistic forecast assumes a constant 0.6 percent monthly increase in HPI. The autoregressive forecast continues the recent HPI movements of the last 4 quarters. The limited foresight forecast follows perfect foresight for 6 months and then reverts to a flat HPI forecast for the remaining 18 months. Each of the forecasts are assumed to revise every three months. ALLL is measured as the level of total allowances over total loan balances.

4.2 Imperfect Forecasts

It is not surprising that CECL with perfect foresight provides more forward-looking provisioning, and this matches results by Covas and Nelson (2018) (figures 8 and 9). However, banks will not be able to perfectly assess macroeconomic conditions. Instead, risk managers must condition on a specific forecast with possible bias and uncertain quality. Here we examine the impact on ALLL from three different forecast methods.

Figure 6 shows ALLL under the optimistic forecast. Home prices are assumed to rise by 0.6 percent each month following California's average county level growth rate. 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 CECL. Predictably, ALLL is below that of the level described by CECL with perfect foresight (blue) given the lower predictions of LTV under an optimistic path.

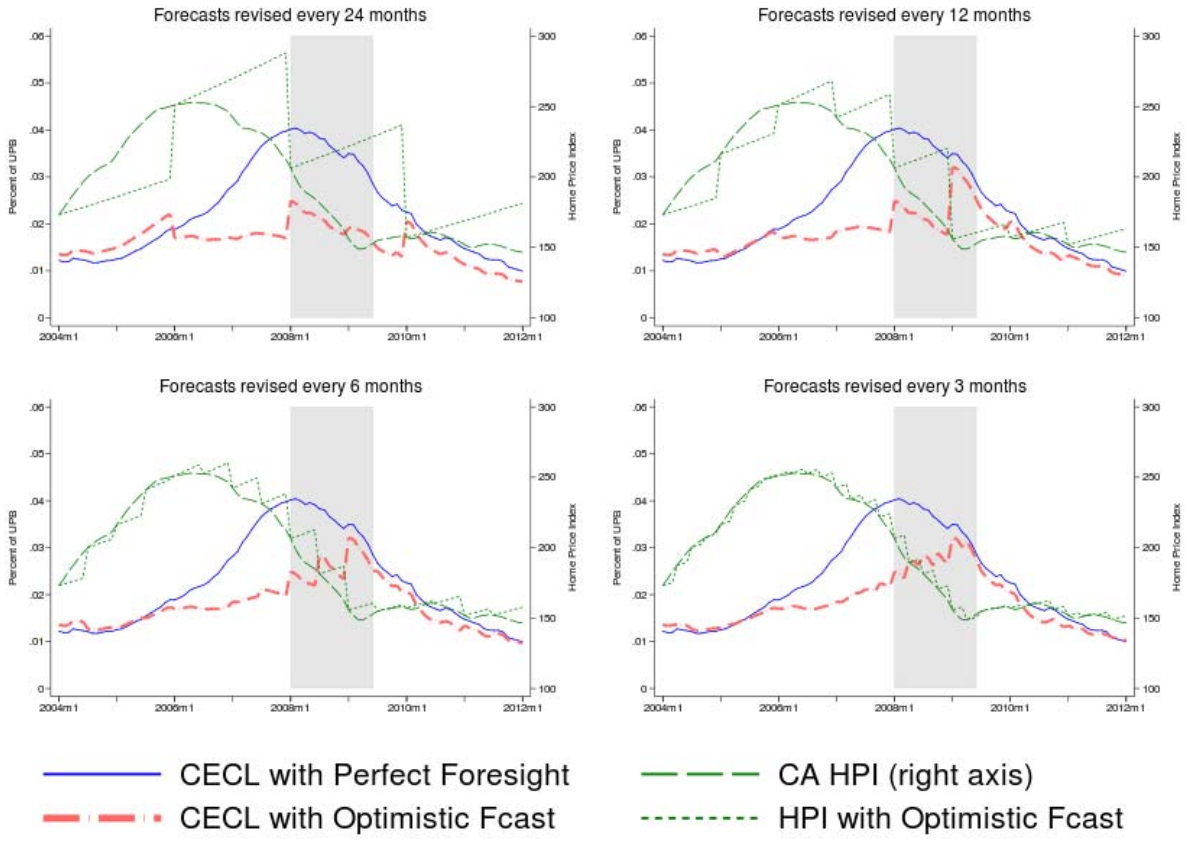
Each panel in figure 6 also represents a different revision frequency. To increase accuracy, risk managers may decide to frequently revise their forecasts and anchor to current conditions given more recent information on the macro-environment. The timing of when these revisions occur is also likely to 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 to the actual conditions and adjusts accordingly. Shown in figure 6 are update schedules at the 24, 12, 6, and 3 month intervals.[17]

With lower frequency revisions, provisioning given an optimistic forecast is somewhat volatile as ALLL moves significantly following each revision. This is especially true in periods of large home price movements where the stale forecast frequently diverges from current conditions. As the forecasts deviates further from current conditions, ALLL under CECL is prone to volatile adjustments that necessitate sharp changes in expected losses. During downturns when forecast revisions are anchored to deteriorating economic conditions, this may increase pro-cyclicality

[17] Note that banks will be required to update forecasts quarterly for financial statements. These other frequencies are meant to demonstrate the effect of delaying more complete updates to a forecast. For example, firms may have more comprehensive budget and strategic reviews on an annual basis.

and resemble provisioning under the incurred loss standard. However, this volatility is smoothed at higher frequencies where the cost of stale forecasts is smaller.[18]

Figure 6: Alternative Forecast – Optimistic



Source: Federal Reserve Board, Form FR Y-9C, Consolidated Financial Statements for Bank Holding Companies; Equifax Credit Risk Insight Servicing and Black Knight McDash Data; and author calculations

Note: CECL with perfect foresight of macroeconomic conditions shows ALLL under the estimated expected loss model. The model conditions on the actual path of home prices in the following two years, afterwards reverting back to the long run experience. The optimistic forecast assumes a constant .6 percent monthly increase in HPI. 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 out to two years from the point of origin.

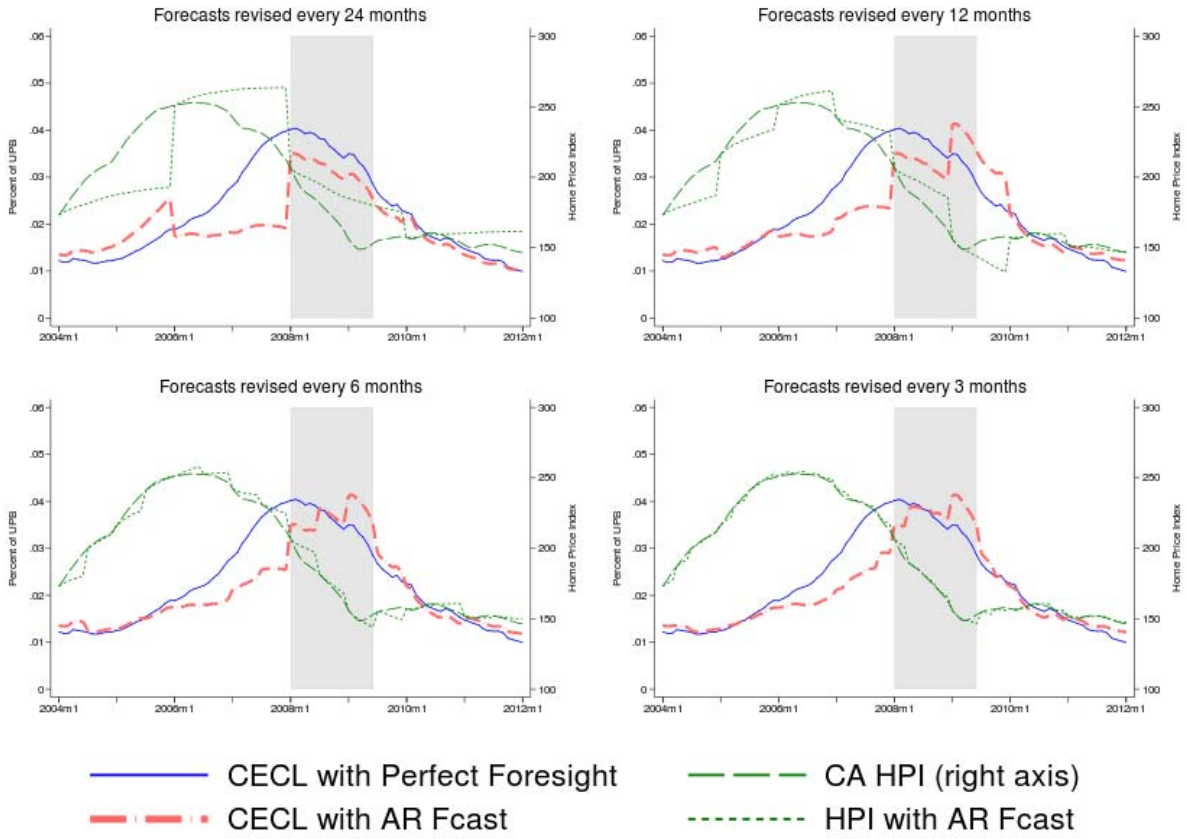
ALLL under the optimistic forecast is less forward-looking than CECL with perfect foresight. Even with forecasts revised every three months, provisions are increased only after home prices have fallen significantly; the quarter of largest percentage increase occurs in 2009Q1 compared

[18] In figure 6, 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 green lines appear similar.

to 2006Q4 with perfect foresight as shown in table 1 (columns 2 & 3). Optimistic forecasts have a more pro-cyclical relationship with home prices and net charge-offs as well as higher volatility. Additionally, a substantial portion of the trough-to-peak increase occurs after 2008Q1 when bank revenues were under heightened stress.

Optimistic CECL is somewhat similar to ALLL under the incurred loss standard – both exhibit buildup throughout 2008 and 2009 as home prices approach the bottom. As summarized in table 1, both increase ALLL primarily after 2008 with 51 percent (0.67/1.3) of the increase for optimistic CECL occurring after 2008Q1 compared to 82 percent (3.01/3.65) under incurred. The quarter of largest percentage increase, 2009Q1, is also close to that of 2008Q4 under the incurred loss standard. On the other hand, optimistic CECL is less correlated with HPI and net charge-offs.

Figure 7: Alternative Forecast - Autoregressive



Source: Federal Reserve Board, Form FR Y-9C, Consolidated Financial Statements for Bank Holding Companies; Equifax Credit Risk Insight Servicing and Black Knight McDash Data; and author calculations

Note: CECL with perfect foresight of macroeconomic conditions shows ALLL under the estimated expected loss model. The model 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 HPI 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 out to two years from the point of origin.

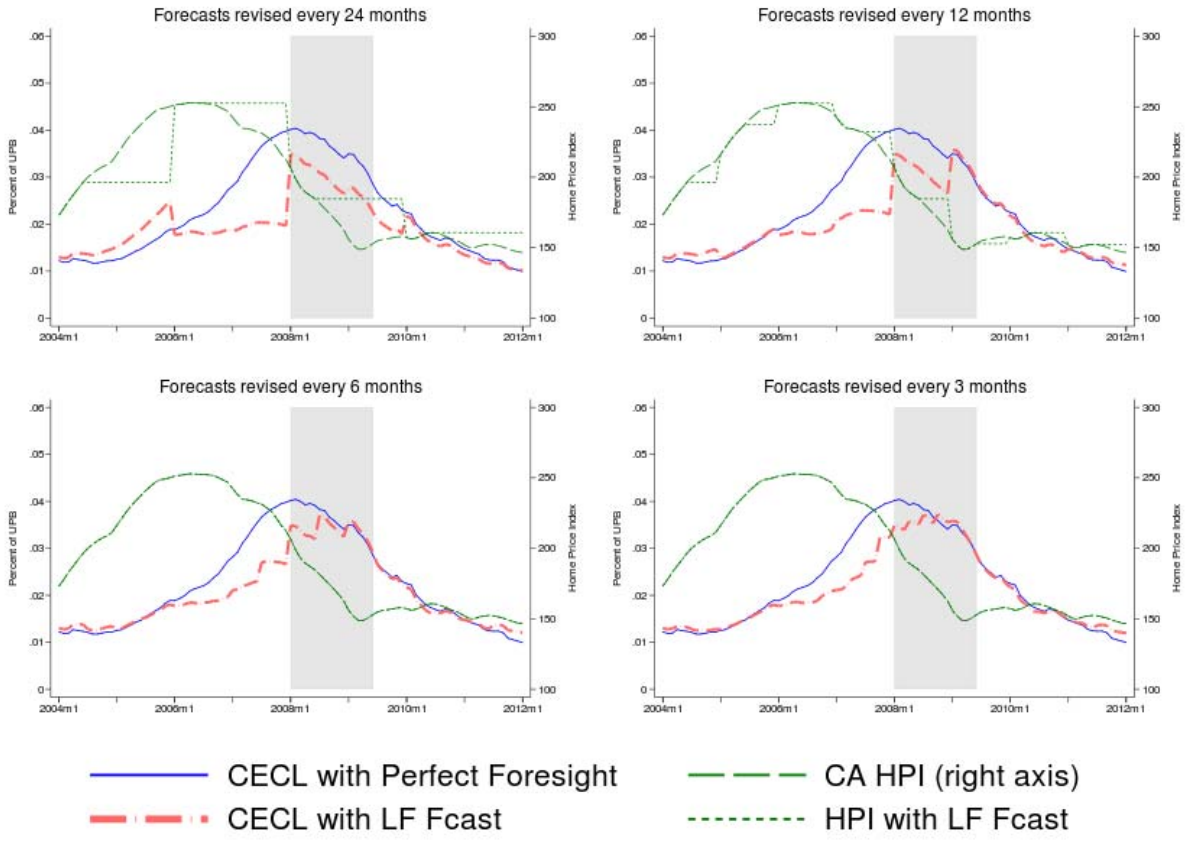
Next we examine the autoregressive forecast that continues recent price trends. Again, we plot this for 24, 12, 6, and 3 month update windows. Figure 7 shows that the autoregressive forecast leads to different patterns than the perfect foresight or optimistic forecasts. With an AR forecast, recent trends are assumed to continue so that downturns are worsened and recoveries are magnified. Generally speaking, ALLL established under AR forecasts will miss inflection and turning points, resulting in more pro-cyclical patterns.

Provisioning is below the level of ALLL under perfect foresight prior to 2008 as the AR specification exhibited less conservative forecasts compared to actual HPI, similar to the

optimistic scenario. From 2008 to 2009, the two largely mirror each other as the AR forecast accurately fits the actual path of home prices. After 2009 however, there is a volatile increase as ALLL is forecast to be much higher due to the continued weakening of home price forecasts compared to the actual low point. 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 more pro-cyclical and less forward-looking. ALLL under an AR forecast, even with high-frequency revisions, has a greater pro-cyclical relationship with HPI and net charge-offs; volatility is higher; and ALLL buildup is faster and more volatile than under perfect foresight. However, compared to ALLL under the incurred loss standard, CECL with the AR forecast still exhibits an earlier reserve buildup going into the downturn with lower volatility and reduced correlation with HPI and net charge-offs. Table 1 (column 4) indicates that CECL under an AR forecast builds up 25 percent (0.55/2.24) of the total trough-to-peak *after* 2008Q1 compared to 82 percent under incurred. The quarter of largest percentage increase occurs in 2008Q1, which is three quarters earlier than that under incurred.

Figure 8: Alternative Forecast – Limited Foresight



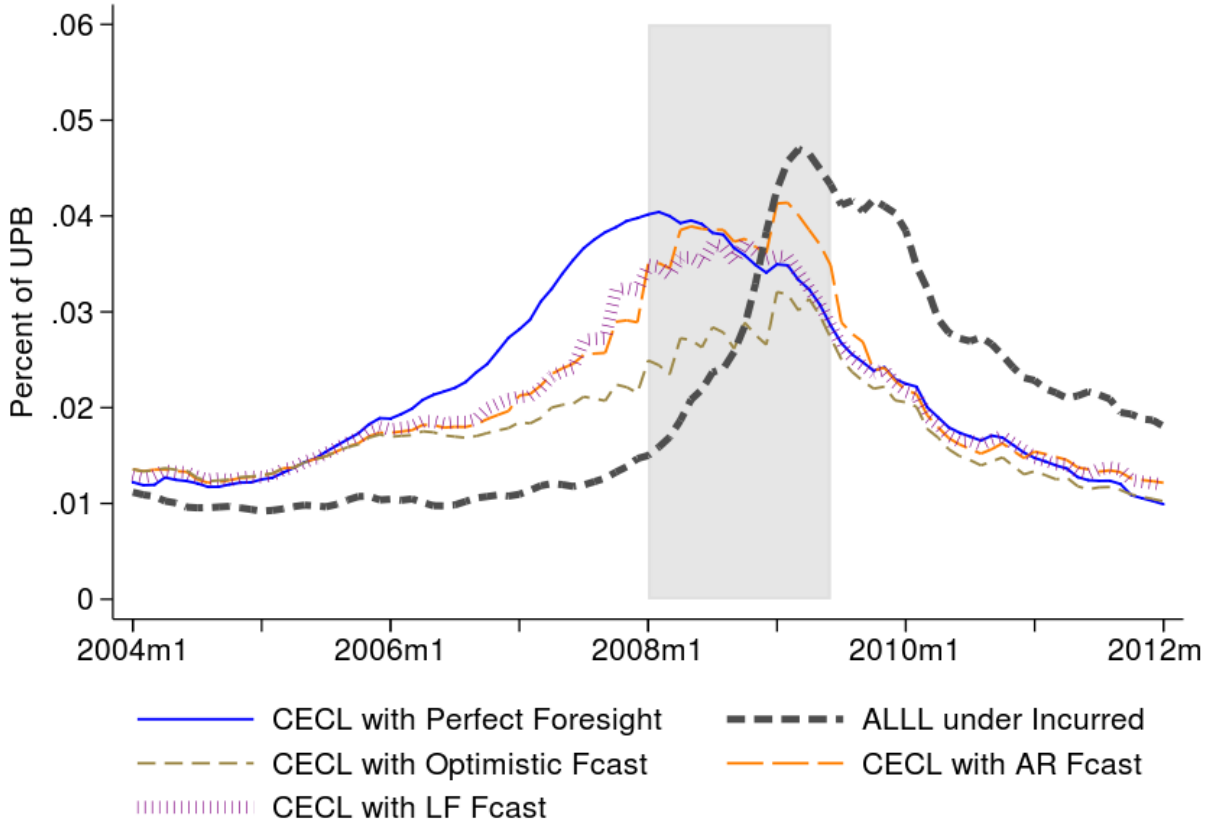
Source: Federal Reserve Board, Form FR Y-9C, Consolidated Financial Statements for Bank Holding Companies; Equifax Credit Risk Insight Servicing and Black Knight McDash Data; and author calculations

Note: CECL with perfect foresight of macroeconomic conditions shows ALLL under the estimated expected loss model. The model conditions on the actual path of home prices in the following two years, afterwards reverting back to the long run experience. The limited foresight forecast follows perfect foresight for 6 months and then reverts to a flat HPI forecast for the remaining 18 months. 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 out to two years from the point of origin.

The third and last forecast method presented in this paper represents a risk manager with a limited ability to predict the future. Forecasts are accurate for 6 months, 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, particularly at high-frequency revisions. As shown in table 1 (column 5), ALLL is built earlier in the economic cycle – only 1 percent (0.02/1.75) of the trough-to-peak buildup occurs *after* 2008Q1 compared to 25 percent under an AR forecast, 51 percent under an optimistic forecast, and 82 percent under incurred. At the trough of the downturn, CECL with limited foresight does not exhibit volatile increases in provisioning and

generally follows ALLL under perfect foresight. To the extent that risk managers have an ability to forecast the future, even for limited time periods, it is likely to lead to a decrease in the degree of pro-cyclical provisioning.

Figure 9: Comparison of Alternative 2-Year Forecasts with 3 Month Revisions



Source: Federal Reserve Board, Form FR Y-9C, Consolidated Financial Statements for Bank Holding Companies; Equifax Credit Risk Insight Servicing and Black Knight McDash Data; and author calculations

Note: CECL with perfect foresight of macroeconomic conditions shows ALLL under the estimated expected loss model. The model conditions on the actual path of home prices in the following two years, afterwards reverting back to the long run experience. ALLL under incurred represents loan-level reserves interpolated using Y-9C data from bank's ALLL as a function of charge offs and loan defaults. The optimistic forecast assumes a constant .6 percent monthly increase in HPI. The autoregressive forecast continues the recent HPI movements of the last 4 quarters. The limited foresight forecast follows perfect foresight for 6 months and then reverts to a flat HPI forecast for the remaining 18 months. Each of the forecasts are revised every three months.

Figure 9 shows the three alternative forecasts together with perfect foresight and ALLL under the incurred loss method. While each of the CECL forecasts, including the optimistic, is generally less pro-cyclical than under incurred loss, the figure illustrates the large range of ALLL under

different forecasts. This range is despite the same underlying model and data. At the beginning of the recession in late 2007, ALLL under perfect foresight would have been more than 1.5 percentage points higher than under the optimistic forecast and roughly 0.5 percent higher than the autoregressive or the limited foresight. As expected, CECL with perfect foresight is the least pro-cyclical with lower volatility and correlation with HPI and net charge-offs. However, generally speaking, each of the forecasts is still less pro-cyclical than under the incurred loss standard. ALLL increases earlier with a larger percentage of trough-to-peak buildup occurring prior to 2008Q1 with less volatility.

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 of losses, 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 portfolio 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 that is free of assumptions regarding the future. But if forecasts are imperfect or 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. For example, across the CECL forecast methods (columns 2-5 of table 1), the correlation with HPI ranges from -18 percent to 11 percent. The correlation with NCO ranges from 25 percent to 57 percent.

Compared to the dispersion in unemployment projections shown in figure 2, if home price forecasts show the same variability, then allowances are likely to show even larger variations. By introducing additional modeling decisions into the calculation of expected loan losses, even ignoring underlying changes in model or data, the link between ALLL and portfolio risk is weakened. Given the same underlying portfolio risk, this may hinder comparability across banks, making it difficult for the market to disentangle portfolio risk from forecast uncertainty. However, Wheeler (2017) develops a measure of lifetime expected credit losses and finds that ALLL understatements relative to expected losses are negatively associated with bank stock

prices. This suggests that market participants may have some ability to deduce the appropriateness of an allowance relative to risk in bank loan portfolios.

4.3 Alternative Durations of the Forward-Looking Period

Additionally, we can examine alternative durations of the reasonable and supportable forecast window. For the analysis in the prior section, the primary economic variable, home price growth, was forecasted for two years after which the loan-level model reverted to only conditioning on factors available as of origination instead of refreshed LTV that accounts for current and forecasted conditions. This can also be interpreted as reverting back to historical experience or a "typical" macroeconomic environment. This forecast window, if changed, could also increase or decrease the variability of provisions across estimation methods.

In the limiting case of immediate reversion to the long-run macroeconomic environment, loss forecasts would not be sensitive to forecasts and only condition on historical behaviors. Figure 10 shows four projection windows: three-year, two-year, one-year, and six-month. Decreasing the projection window and reducing the importance of the forecasts flattens ALLL and the path becomes less forward-looking. At shorter windows, there is little difference between the different foresights because all quickly revert to the long-run macroeconomic environment.

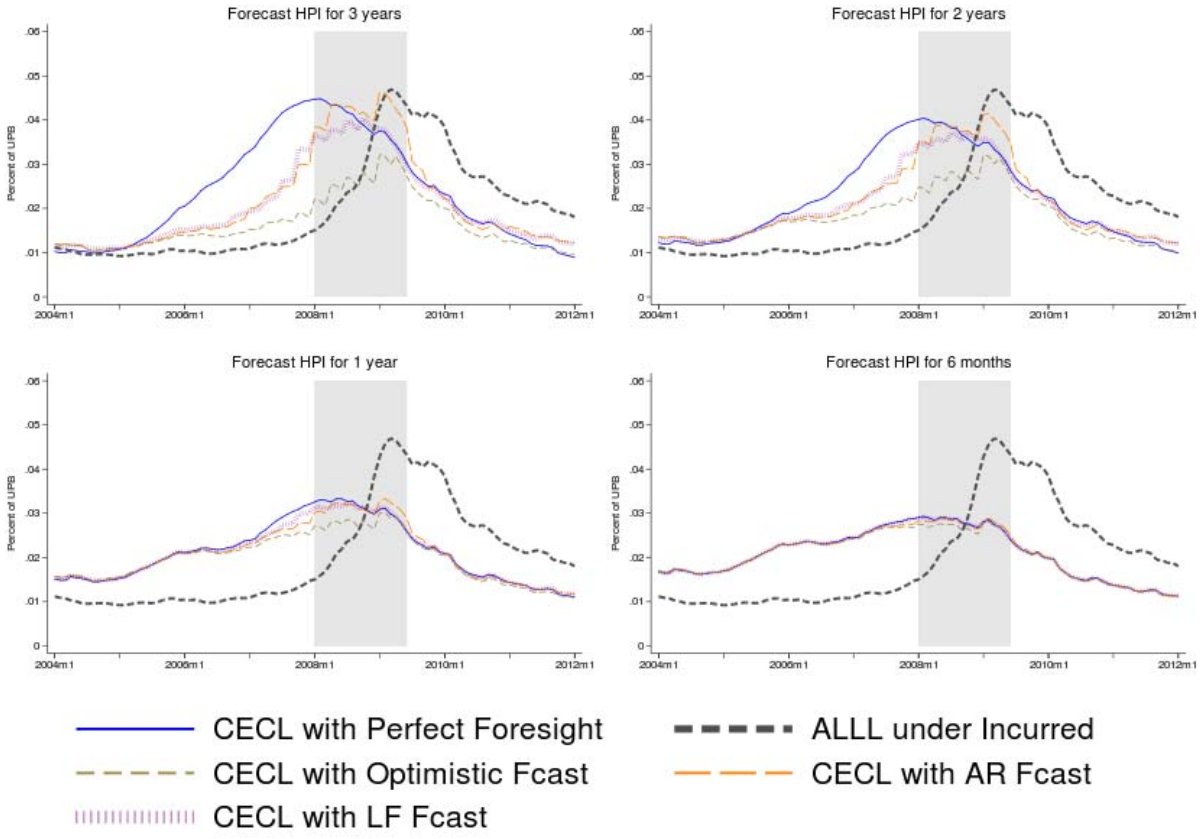
This behavior reverses at longer forecast periods. At the three-year window, the variation across forecasts is enlarged. As the window continues to increase, volatility will increase as ALLL becomes more responsive to small perturbations in forecasts which may diverge significantly from actual conditions in the future. Reverting back to historical experience constrains some of the costs of low-quality forecasts.

The use of different reversion periods could also result in greater variation in allowances. Recall that CECL allows for a transition period between the reasonable and supportable forecast window and reverting to the historical experience. The analysis in this paper uses an immediate reversion, if pre-recession forecasts are too optimistic, using a reversion period will lead to more pro-cyclical results as the forecast requires a longer amount of time to return to the historical experience.

These forecast window and reversion assumptions are important drivers of the differences between our results and those of Covas and Nelson (2018). By using a 3-year forecast period

plus a reversion period that often lasts longer than a year, Covas and Nelson are extending the period by which each new forecast can lead to severe changes in ALLL. Partly as a result, their results show much stronger pro-cyclicality under CECL. Their modeling exercises demonstrate the loss of forecasting power between 2 years and 3 years (figures 2 and 3). Given the known challenges in forecasting, it is hard to motivate a reason to extend the forecast further with a long reversion period. Finally, Covas and Nelson use a VAR model. By design, these models will miss inflection points as shown in the AR results presented here. Our AR results show less pro-cyclicality than incurred (table 1), but the performance diminishes when switching from a 2-year forecast to a 3-year forecast (figure 10).

Figure 10: Comparison of Alternative Forecast Windows



Source: Federal Reserve Board, Form FR Y-9C, Consolidated Financial Statements for Bank Holding Companies; Equifax Credit Risk Insight Servicing and Black Knight McDash Data; and author calculations

Note: Each panel shows a forecast period of x years. CECL with perfect foresight of macroeconomic conditions shows ALLL under the estimated expected loss model. The model conditions on the actual path of home prices in the following x years, afterwards reverting back to the long run experience. ALLL under incurred represents loan-level reserves interpolated using Y-9C data from bank's ALLL as a function of charge offs and loan defaults. The optimistic forecast assumes a constant .6 percent monthly increase in HPI. The autoregressive forecast continues the recent HPI movements of the last 4 quarters. The limited foresight forecast follows perfect foresight for 6 months and then reverts to a flat HPI forecast for the remaining months. Each of the forecasts are revised every three months.

4.4 Alternative State Analysis

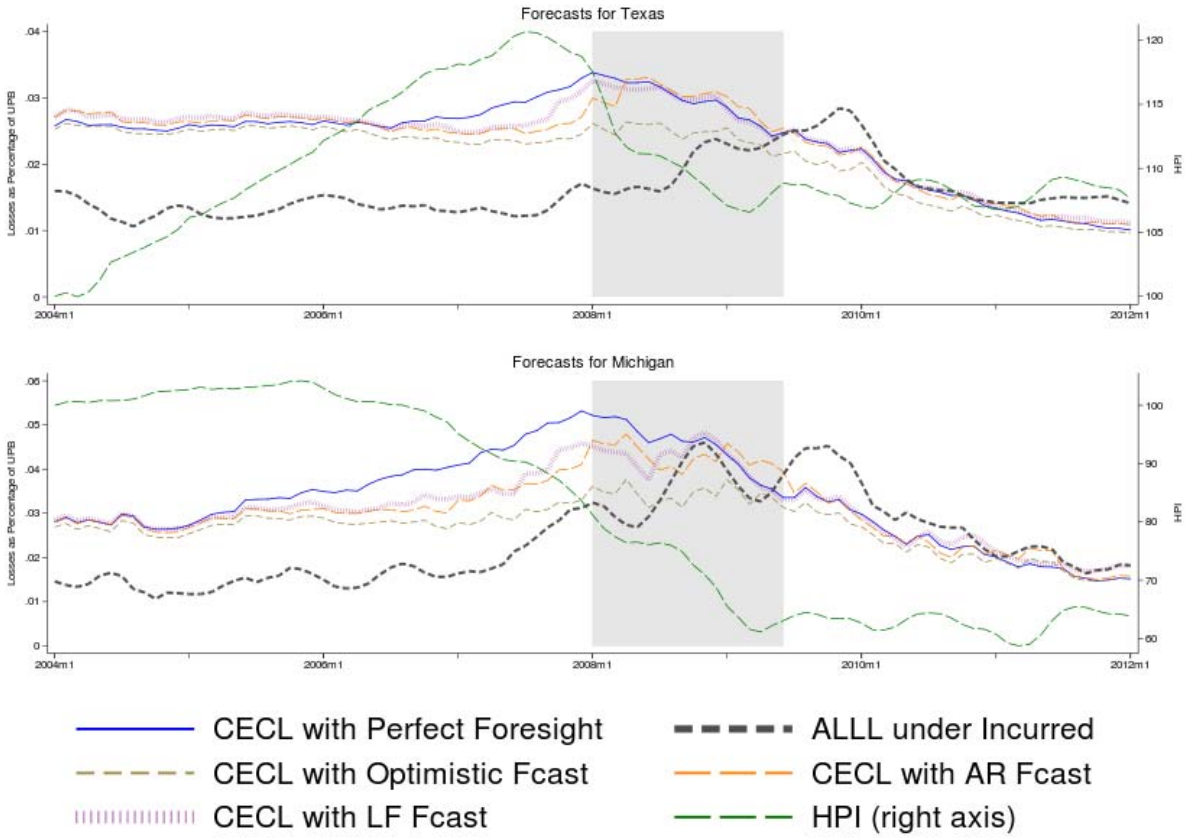
As a robustness check, we repeat our analysis for two additional states, Texas and Michigan, which exhibited slightly different house price paths during the financial crisis. Figure 11 shows the home price paths for the two states in green. Texas home prices increased slower than prices in California and peaked roughly 18 months afterwards. Additionally, Texas did not exhibit the same fall in prices during the recession. Michigan, however, never saw the pre-crisis increases in

home prices as in California and Texas but instead saw decreases fairly monotonically from 2004 through the end of the recession.

Figure 11 also shows the CECL forecasts across the methods used above. The relationship of the forecasts to home price paths are illustrative. For Texas, CECL with perfect foresight of the macroeconomic conditions is relatively flat, which corresponds to the relative stability of HPI in Texas. The three alternative forecasts also show a similar contour which perhaps indicates that Texas had more predictable home prices under the methodologies considered here compared to California. Michigan on the other hand shows more variation between the different forecasts as the autoregressive, optimistic, or the limited foresight forecasts do relatively worse compared to perfect information. The alternative ALLL paths are more volatile and are more pro-cyclical compared to CECL with perfect foresight. This is likely related to the pre-crisis fall in home prices, which was not sufficiently captured by the alternative forecast models. Overall, in instances where forecast models are better able to predict future conditions, ALLL is likely to be smoother and more forward-looking.

However, compared to the incurred loss standard, ALLL under the alternative forecasts still behave in a less pro-cyclical fashion. Provisions are more forward-looking and increase in a less volatile manner prior to the crisis when bank earnings are less stressed. While the underlying quality of forecasts may differ across methodologies, high-frequency revisions allow CECL to revise forecasts to deteriorating conditions when entering a downturn. This anchoring to actual data means that even biased forecasts, such as the optimistic model, are likely to be less volatile and pro-cyclical compared to ALLL under incurred loss.

Figure 11: Comparison of Forecasts for Texas and Michigan



Source: Federal Reserve Board, Form FR Y-9C, Consolidated Financial Statements for Bank Holding Companies; Equifax Credit Risk Insight Servicing and Black Knight McDash Data; and author calculations

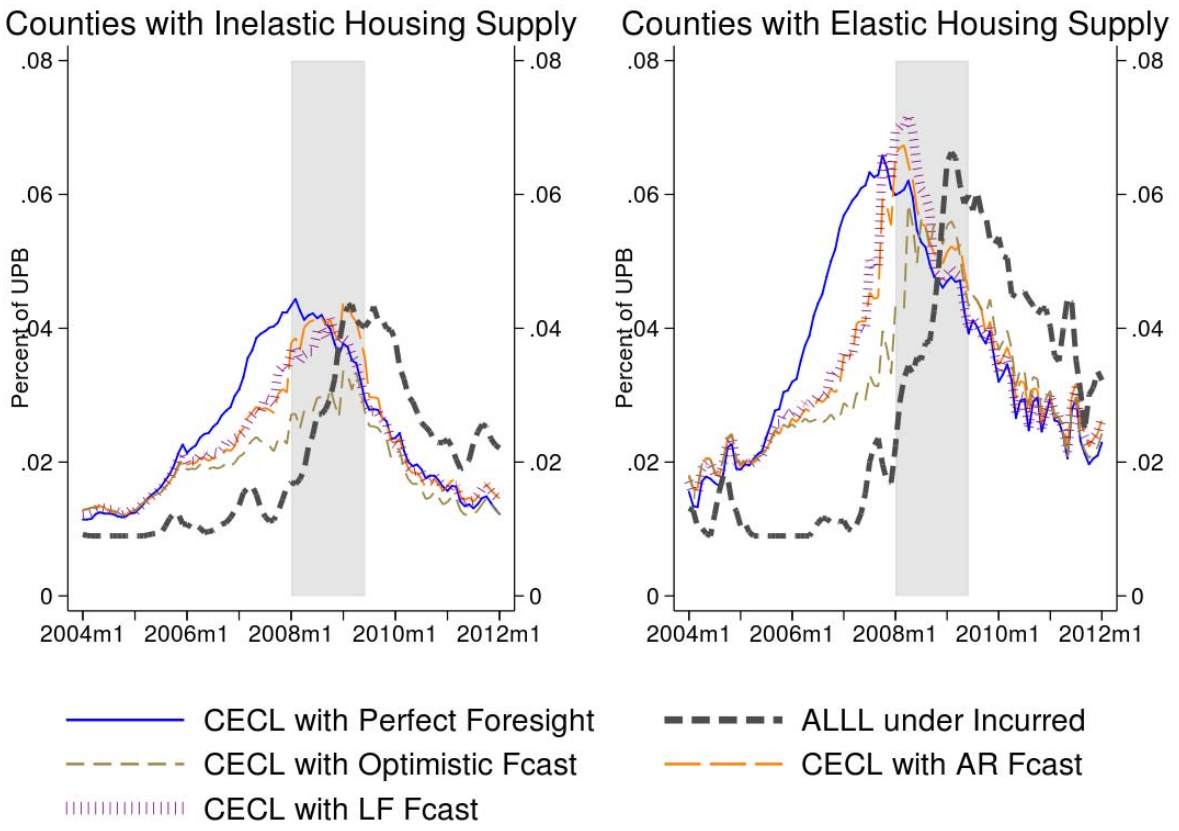
Note: CECL with perfect foresight of macroeconomic conditions shows ALLL under the estimated expected loss model. The model conditions on the actual path of home prices in the following two years, afterwards reverting back to the long run experience. ALLL under incurred represents loan-level reserves interpolated using Y-9C data from bank's ALLL as a function of charge offs and loan defaults. The optimistic forecast assumes a constant percent monthly increase in HPI. The autoregressive forecast continues the recent HPI movements of the last 4 quarters. The limited foresight forecast follows perfect foresight for 6 months and then reverts to a flat HPI forecast for the remaining 18 months. Each of the forecasts are revised every three months. The HPI index for Texas and Michigan are standardized at 100 as of January 2004. Following Goodman and Zhu (2015), we apply an LGD of 21.4 percent for Texas and 50.6 percent for Michigan.

4.5 Analysis on Counties with Inelastic Housing Supply

We also do a robustness check to see if certain characteristics of the local housing market could change the timing of reserves across the forecast methods. Specifically, we look at housing markets that have elastic or inelastic supply. Using the methodology of Saiz (2010), we divide the CA counties into two groups: those below and above the median county's supply elasticity. For each group we run the various forecasts. The results are shown in figure 12. Not surprisingly, the level of reserves is much different across the two elasticity groups. However, the relative

timing or order across the reserving methods is generally the same as those of the baseline results above. For example, the left graph shows forecasts for the counties with inelastic housing supply. CECL with perfect foresight increases the earliest and peaks first. CECL with limited foresight and the AR forecast have roughly the same timing. The optimistic forecast and the incurred method come last. This order is about the same for counties with elastic housing supply (the right side of figure 12). However, the optimistic forecast peaks earlier than the incurred method. Overall, CECL forecasts are less pro-cyclical than the incurred method.

Figure 12: Comparison of Alternative Forecasts by Home Supply Elasticity



Source: Federal Reserve Board, Form FR Y-9C, Consolidated Financial Statements for Bank Holding Companies; Equifax Credit Risk Insight Servicing and Black Knight McDash Data; Saiz (2010); and author calculations

Note: Analysis constrains sample to Californian counties with supply elasticities below and above the median county's supply elasticity. Supply elasticities are taken from the methodology of Saiz (2010). CECL with perfect foresight of macroeconomic conditions shows ALLL under the estimated expected loss model. The model conditions on the actual path of home prices in the following two years, afterwards reverting back to the long run experience. ALLL under incurred represents loan-level reserves interpolated using Y-9C data from bank's ALLL as a function of charge offs and loan defaults. The optimistic forecast assumes a constant .6 percent monthly increase in HPI. The autoregressive forecast continues the recent HPI movements of the last 4 quarters. The limited foresight forecast follows perfect foresight for 6 months and then reverts to a flat HPI forecast for the remaining 18 months. Each of the forecasts are revised every three months.

5. Conclusion

CECL is a major change 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, our analysis suggests CECL will lead to more forward-looking loan loss provisioning, under various measures of pro-cyclicality, than the incurred loss standard if risk

managers have at least some capacity to predict near-term macroeconomic trends. Even poor forecasts that are frequently revised and anchored to actual economic conditions will result in more forward-looking loan loss reserves. That feature should dampen the degree to which reserves are overstated at the trough of an economic cycle and understated at its peak, resulting in earlier reserve buildup when entering a downturn.

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 home price forecast. Controlling for portfolio composition, we find that differences in the methodology used to construct forecasts, differences in the timing of revisions, and differences in the length of the forecast window can have nontrivial effects 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.

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Appendix A

Origination and Refreshed Mortgage Model

	Origination Model		Refreshed Model	
Coefficient	**Prepay**	**Default**	**Prepay**	**Default**
FICO® Score				
580 - 619	1.1	0.86	1.11	0.81
	(0.17)	(0.11)	(0.17)	(0.10)
620 - 679	1.38**	0.46***	1.41***	0.43***
	(0.18)	(0.05)	(0.18)	(0.05)
680 - 719	1.40***	0.28***	1.40***	0.30***
	(0.18)	(0.03)	(0.18)	(0.04)
720 - 779	1.40***	0.11***	1.40***	0.13***
	(0.18)	(0.01)	(0.18)	(0.02)
Over 780	1.50***	0.043***	1.49***	0.054***
	(0.19)	(0.01)	(0.19)	(0.01)
LTV				
40-50%	1.13	1.3	1.03	1.48
	(0.09)	(0.51)	(0.07)	(0.68)
50-60%	1.02	1.33	1.04	1.97
	(0.08)	(0.47)	(0.07)	(0.82)
60-70%	1.02	1.75*	1.04	3.48***
	(0.08)	(0.60)	(0.07)	(1.38)
70-75%	0.97	2.21**	1.03	4.51***
	(0.08)	(0.77)	(0.07)	(1.82)
75-80%	0.95	2.43**	0.93	5.24***
	(0.07)	(0.85)	(0.07)	(2.10)
80-85%	0.91	2.63***	0.94	8.41***
	(0.07)	(0.94)	(0.07)	(3.32)
85-90%	0.80**	2.99***	0.82**	9.62***
	(0.08)	(1.09)	(0.07)	(3.79)
90-95%	0.75***	3.15***	0.69***	11.4***
	(0.07)	(1.15)	(0.06)	(4.49)
95-100%	0.59***	3.83***	0.79**	14.0***
	(0.06)	(1.39)	(0.07)	(5.54)
100-120%	0.65***	4.59***	0.44***	19.8***
	(0.08)	(1.74)	(0.04)	(7.71)
Over 120%	0.55	10.7**	0.29***	31.8***
	(0.39)	(11.70)	(0.05)	(12.70)
Observations	480,564	480,564	480,564	480,564
Pseudo R^2	5%	5%	6%	6%

Source: Equifax Credit Risk Insight Servicing and Black Knight McDash Data; and author calculations.
Note: Additional controls include seasoning indicators for each payment month, original home value, original loan amount, monthly payment increase and decrease, cash-out refinance indicator, non-cash-out refinance indicator, not full documentation indicator, and unknown documentation indicator. Estimation sample includes US 30 year, fixed-rate, first-lien mortgages that are portfolio-held on bank's balance sheets. Displayed coefficients are odds ratios. * p<.1, **p<.05, *** p<.01

Appendix B

Because loan-level provisioning and ALLL data is not available for our sample of Californian mortgages, we extrapolate what ALLL would have looked like for this sample of loans using aggregate provisioning data from the Y-9C. From the Y-9C, we further restrict to those banks that have greater than 30 percent of their loan portfolio in first-lien mortgages to focus on ALLL behavior reflecting heavy concentrations of mortgage risk. The results are not quantitatively different if we include the full universe of Y-9C banks.

The regression model extrapolates the relationship between net charge-offs and ALLL by predicting the stock of ALLL given lagged and leading values of net charge-offs. We use limited leading information on charge-offs to better model the relationship between the ALLL and net charge offs and because banks observe the underlying delinquency event before charging off the loan. These estimates are then applied to the loan losses observed in the estimation sample based on California mortgage losses.

ALLL Extrapolation

	ALLL (Percentage of Loan Balances)
2 Quarter Lead of Charge Off Rate	0.88***
	(0.25)
1 Quarter Lead of Charge Off Rate	0.91***
	(0.32)
Charge Off Rate	0.66**
	(0.32)
1 Quarter Lag of Charge Off Rate	0.80**
	(0.32)
2 Quarter Lag of Charge Off Rate	-0.15
	(0.32)
3 Quarter Lag of Charge Off Rate	0.38
	(0.32)
4 Quarter Lag of Charge Off Rate	0.16
	(0.25)
Constant	0.0090***
	(0.00068)
Observations	63
R-Squared	0.915

Source: Federal Reserve Board, Form FR Y-9C, Consolidated Financial Statements for Bank Holding Companies.