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CECL and the Credit Cycle

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May 30, 2019

Abstract

We find that that the Current Expected Credit Loss (CECL) standard would slightly dampen fluctuations in bank lending over the economic cycle. In particular, if the CECL standard had always been in place, we estimate that lending would have grown more slowly leading up to the financial crisis and more rapidly afterwards. We arrive at this conclusion by estimating historical allowances under CECL and modeling how the impact on accounting variables would have affected banks' lending and capital distributions. We consider a variety of approaches to address uncertainty regarding the management of bank capital and predictability of credit losses.

JEL Codes: E1, E3, G21, G28, M41, M48
Keywords: Current expected credit loss, Allowance for Loan and Lease Losses, Accounting policy

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The current expected credit losses (CECL) standard will soon replace the incurred loss method (ILM) for the recognition of credit losses in financial accounts.[1] The resulting changes to the timing and magnitude of loss allowances will affect banks' regulatory capital. Since we do not expect significant changes to banks' incentives to manage regulatory capital, we anticipate that CECL will affect banks' lending and capital distributions. As the date of implementation approaches, several commentators have raised concerns that the standard will have a "procyclical" impact, reducing lending in downturns in particular. In contrast, the findings in this study suggest that CECL will modestly affect bank lending in a way that dampens fluctuations.[2]

We arrive at this conclusion through a simple model of the hypothetical impact of CECL on U.S. bank lending over 1998-2014. As inputs to this approach, we estimate both historical loss allowances under CECL and the response of bank lending and capital plans to these changes in allowances. We consider a range of approaches to deal with uncertainty. Specifically, we estimate CECL allowances under three different assumptions about the predictability of credit losses, and use estimates of bank adjustments to changes in capital buffers from academic literature in addition to our own. To keep our analysis straightforward, we model lending at the bank-level and assume the composition of bank lending is unaffected by CECL.

The impact of credit loss accounting on the credit cycle depends on both the timing and magnitude of loss allowances. If CECL results in a larger increase in loss allowances around recessions, a greater amount of deleveraging occurs. However, as loss recognition occurs earlier under CECL, a greater share of the deleveraging occurs prior to—rather than during—the recession. Our conclusion that CECL is likely to be slightly less procyclical than ILM accounts for both potential effects. We reach this conclusion despite the simplifying assumptions we employ that generally weaken CECL's potential to reduce cyclicality.

In our model, CECL merely shifts lending to a later point in the economic cycle, leaving long-run average loan growth unaffected. In our preferred specification, we estimate that this shift slightly reduces U.S. lending growth volatility over the period 1998 through 2015, while slightly worsening the largest peak-to-trough decline in bank lending. CECL reduces fluctuations in lending further when predictability of losses is greater or banks adjust their capital ratios more

[1] See Section I and Cohen and Edwards (2017) for further background on expected credit loss standards.
[2] For empirical work connecting bank loan supply with macroeconomic outcomes, see for example Peek and Rosengren (2000) and Bassett et al. (2014).

rapidly. Conversely, in our framework, CECL has no effect on lending when banks do not respond to its impact on regulatory capital.

Other studies generally find that forward-looking or expected loss provisioning are less procyclical than ILM.[3] Specifically, Beatty and Liao (2011) and Cummings and Durrani (2016) associate forward-looking provisioning practices with stronger lending in downturns, while Bushman and Williams (2012) find more active risk-management under more forward-looking provisioning. DeRitis and Zandi (2018) argue that CECL should reduce cyclicality by constraining fluctuations in lending standards.[4] Since our approach abstracts from any impact of CECL on the composition of bank lending, this literature suggests that our approach makes CECL appear more procyclical than it is.

Three papers suggest that CECL's impact on capital in the early stages of a recession could make the standard more procyclical than ILM (Abad and Suarez 2018, Covas and Nelson 2018, and Ryan 2019). Of these papers, only Covas and Nelson (2018) quantifies the impact on lending, and argues that CECL would have caused a significantly greater decline in lending during the financial crisis. We show in Section IV that this conclusion results largely from the authors' assumption that banks wait until the peak of the downturn to respond to the capital impact of CECL.

In Section I, we provide background discussion of the CECL standard. Section II provides an overview of the framework we follow, and Sections III and IV describe our approaches to estimating the accounting and economic impact of CECL in detail. We discuss caveats to our analysis in Section V, and Section VI concludes.

I. The Current Expected Credit Loss (CECL) Standard

The CECL standard requires institutions applying U.S. Generally Accepted Accounting Principles (GAAP) to hold loan loss allowances equal to expected credit losses for the lifetime of

[3] An additional literature generally finds that dynamic provisions have some potential to improve macroeconomic stability (Jimenez et al 2017, Agenor and da Silva 2017, Agenor and Zilberman 2015, and Bouvatier and Lepetit 2012). However, dynamic provision policies do not generally reflect either incurred or expected losses.

[4] Specifically, they argue that poor quality mortgage originations in the mid-2000s would have greatly elevated allowances under CECL well in advance of the losses, and that these high allowance requirements would have inhibited the growth of subprime lending that ultimately exacerbated the downturn.

each loan.[5] CECL was issued by the Financial Accounting Standards Board (FASB) on June 16, 2016. It will go into effect as part of U.S. GAAP for fiscal years starting after December 15, 2019, at which point it will cover most large U.S. banks.[6] CECL replaces ILM, which requires that allowances cover losses related to incurred credit impairments.

CECL was introduced largely to address concerns that loan loss reserves under ILM are "too little, too late." In the lead up to the financial crisis, credit losses remained low despite declining mortgage lending standards. As losses remained low, even as the economy slowed and home prices began to fall, loan loss allowances under ILM remained low as well. By the time allowances began to rise significantly at the end of 2007, the economy had entered a recession and the market value of bank equity had declined by one-third, and by early 2009 the market value of U.S. bank equity was less than half of the book value. Under these circumstances, it seems likely that a forward-looking standard for loan loss recognition has the potential to better align bank capital with economic reality.[7]

Under CECL, firms are required to forecast the runoff of loan balances—due to maturity, prepayment, and amortization, as well as certain loan extensions—as well as charge-off and recovery rates. Due to the emphasis on forecasts, most firms will need to add to or adapt their current loss estimation approaches. Regulatory expectations for model complexity are likely to depend on the size of the firm. Many large banks have indicated they plan to adapt much of the modeling and data infrastructure used in stress testing for CECL. In contrast, regulators have suggested that small banks may be able to comply with the standard through adjustments to current existing allowance methods.[8] Given the range of approaches expected, it is difficult to model the firm-specific impact of CECL.[9]

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[5] CECL covers all financial instruments carried at amortized cost, including loans, leases and held-to-maturity securities.

[6] The CECL implementation date is later for non-SEC filing and non-public business entities. The CECL issuance announcement, dated June 16, 2016 can be found here: https://www.fasb.org/cs/ContentServer?c=FASBContent_C&cid=1176168232900&d=&pagename=FASB%2FFASBContent_C%2FNewsPage. Note that banks have the option to phase in the impact of CECL on regulatory capital over a three-year period. See the Federal Register announcement dated December 18, 2018: https://www.occ.treas.gov/news-issuances/news-releases/2018/nr-ia-2018-142a.pdf

[7] However, Ryan (2019) argues that by counting losses over the full expected lifetime of the loan, CECL worsens the mismatch in the treatment of future expected revenues and losses.

[8] See pg. 11 of Federal Reserve SR 19-8 at https://www.federalreserve.gov/supervisionreg/srletters/sr1908a1.pdf

[9] For a discussion of variability in CECL modeling and implementation, see Du et al. (2018) and Chae et al. (2018).

Many other countries have recently (January 2018) implemented an expected credit loss framework, International Financial Reporting Standards (IFRS) 9.[10] The key conceptual difference between CECL and IFRS 9 is that allowances in IFRS 9 need only cover one year of expected losses for loans that have not experienced significant deterioration in credit quality since origination. Once such deterioration occurs, IFRS 9 requires that allowances cover lifetime expected losses just as CECL does.

II. Overview of the Impact Assessment Framework

Our framework captures a simple and relatively direct impact of CECL on credit availability. CECL directly affects loan loss allowances, which in turn affect banks' income and capital. Since there are no current proposals to change bank capital rules in response to CECL,[11] we assume that banks' capital ratio targets are unaffected by the standard.[12] As a result, we assume that banks make changes to capital distributions and lending to offset CECL's impact on capital ratios. We will characterize CECL as more or less procyclical than ILM based on whether it dampens or exacerbates fluctuations in lending growth.

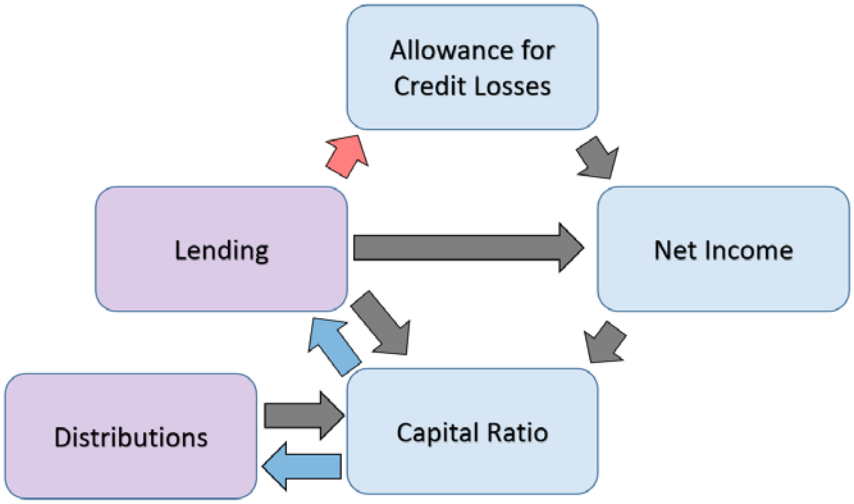
Figure 1 illustrates the relationships we model between the variables affected by loan loss accounting in our framework. The gray arrows represent simple mechanical or rule-based relationships. The colored arrows represent the more complex relationships that require the modeling detailed in Sections III and IV. The red arrow represents our estimates of the impact of CECL on loan loss allowances. The blue arrows represent estimates of banks' adjustments to capital distributions and lending in response to CECL's capital impact. We formalize this framework with a system of equations detailed in Appendix A.

[10] Most large economies currently use IFRS 9. A full list can be found here: https://www.ifrs.org/use-around-the-world/use-of-ifrs-standards-by-jurisdiction/

[11] However, as discussed in Section V, CECL affects CCAR banks' stress capital buffers.

[12] If net income volatility increases under CECL—as some have argued—target buffers might increase. However, if buffers are maintained to also absorb expected future losses, they might not need to be as large under CECL. Discussions with bankers generally suggest that target capital buffers are unlikely to change much.

Figure 1: Impact Assessment Framework



Our framework involves several simplifications. First, we do not capture any effects of CECL that may operate independently of its impact on capital, such as CECL's potential impact on the set of information presented to bank management or investors. Second, we assume that CECL does not affect the composition of bank lending, and has a proportional impact across banks' assets. Third, we do not model loan pricing. Finally, our framework does not capture the indirect (second-order) effects of CECL that follow from the impact of CECL on the subsequent state of the economy. Consistent with these simplifications, we assume that net charge-off rates are unaffected by CECL. Sections V provides further discussion of the caveats to our approach.

III. Impact on Allowances

In this section, we estimate the impact of CECL on the aggregate loan loss allowances of U.S. bank holding companies—the red arrow in Figure 1. We find that CECL accelerates loan loss recognition, but also increases allowances in downturns as compared to the ILM standard. These findings have generally opposing effects on the standard's overall impact on lending cyclicality, which we evaluate further in Section IV.

We estimate CECL allowances separately for each of seven asset classes aligned with regulatory reporting categories: residential real estate, commercial and industrial, commercial real estate, other wholesale, cards, other retail, and auto loans. Except where otherwise stated, our analysis is based on publicly-available data from the universe of lenders in the FR Y-9C.[13] Table 1 breaks the aggregate loan portfolio into these asset classes.

Table 1: Composition of Aggregate Bank Holding Company Loan Portfolio

Asset Class	**Average Share of Aggregate Loan Portfolio[14] (Q2 1986-Q4 2014)**
Residential real estate (RRE)	29.6%
Commercial and industrial (C&I)	25.9%
Commercial real estate (CRE)	20.6%
Cards	8.0%
Other wholesale (excl. C&I, CRE)	7.5%
Other retail (excl. cards, auto, RRE)	4.7%
Auto	3.8%

Source: FR Y-9C and authors' calculations.

Under CECL, allowances equal the expected lifetime credit losses of all loans/leases and held-to-maturity securities. However, in our estimates, we apply several simplifications to this concept that should have only a modest impact. First, we limit the scope by excluding held-to-maturity securities, and do not discount—which the standard allows—future credit losses. These omissions have an offsetting impact on allowance estimates, resulting in little impact in aggregate. In addition, we employ some modeling assumptions to simplify the analysis and handle data limitations. For instance, instead of estimating the future credit losses of the current loan portfolio, we separately estimate the runoff of the portfolio balance and the net charge-off (i.e. loss) rate.[15] Our estimates of portfolio runoff depend only on the asset class of the loan, and not on macroeconomic conditions or characteristics of the portfolio at the specific bank. Due to

[13] We exclude firms with atypical bank business models (average risk weights lower than 20% or higher than 100%, average tier 1 risk based capital ratios above 25% or accounting leverage ratios above 15%, or with loans representing an average of less than 25% of assets). We also exclude firms with fewer than ten quarters of history in the FR Y-9C, such as firms near the minimum asset threshold for reporting. Excluded firms account for an average of 12% of Y-9C filers and within the Y-9C represent 9% of aggregate loans and 17% of aggregate assets. The largest excluded firms typically have loans of less than 25% of assets.

[14] Historically, a less granular breakdown of loan portfolios is available. We impute historical portfolio shares using the assumption that relative portfolio shares are unchanged until they are first reported. These imputations apply to the residential real estate portfolio prior to 2002, commercial real estate prior to 2007, cards prior to 2010 and auto and other wholesale/retail prior to 2011.

[15] This approach does not bias our estimate of lifetime loss if the estimation errors on loan life and loss rate are uncorrelated.

limited historical data at the asset class level, we use forecasts of net charge-off rates that are proportional across asset classes. Furthermore, we lack historical cohort level data, so these forecasts do not account for maturity or changes in portfolio composition across asset classes.[16]

With these simplifications, the equation below represents our estimate of CECL allowance for credit losses (ACL) for asset class *a* of bank *b* at quarter *t*. The coefficient λ_a represents the net chargeoff rate of asset class *a* relative to commercial and industrial loans, i.e. $\lambda_a = {}^{E[NCO_a]}\!/_{E[NCO_{C\&I}]}$.[17] The bank-specific net charge-off rate $\text{NCORate}_{\text{b,t+j}}$ is normalized by the average λ_a of the bank *b* loan portfolio at *t+j*, and is assumed to be the same under CECL as it actually was under ILM.[18]

$$ACL_{bat} = \sum_{k=1}^{\infty} \underbrace{Loans_{bat} * \prod_{j=0}^{k-1} (1 - RunoffRate_{aj} - \lambda_a E_t[NCORate_{b,t+j}])}_{Remaining\ Loans\ after\ k-1\ Quarters} * \underbrace{\lambda_a E_t[NCORate_{b,t+k}]}_{Expected\ Net\ CO\ Rate\ at\ t+k} \quad (1)$$

In the remainder of this section, we describe our approaches to modeling portfolio runoff and expected net charge-off rates, and then compare our estimates of CECL allowances to actual allowances.

A. Loan Balance Runoff

We model the runoff of loan balances at the asset class level. This runoff should reflect balance reduction due to prepayment, amortization, loan expiration at maturity, and extensions due to troubled debt restructuring, though our estimates do not explicitly take account of each of these. Our runoff rate estimates are independent of macroeconomic conditions. We believe this is a relatively immaterial simplification, as most of the variation in lifetime expected loss for the typical loan comes from variation in loss rates, as opposed to variation in loan runoff.

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[16] Seasoning effects can go either way, depending on whether loan amortization or downward credit migration effects dominate. Selection effects tend to suggest lower losses to older loans, as higher risk loans tend to have shorter maturities.

[17] We estimate average aggregate net charge-off rates relative to commercial and industrial loans using the longest time period for which data are available in FR Y-9C for the given asset class. We estimate λ_a of 0.65 for other wholesale, 0.69 for residential real estate, 0.78 for commercial real estate, 1.78 for auto loans, 4.66 for other retail loans and 4.94 for cards.

[18] In making this assumption, we ignore second-order effects on net charge-offs that might result from the impact of CECL on portfolio composition and macroeconomic conditions.

Table 2 presents the average remaining life of loan balance that result from our runoff rates. The table also classifies our approach to the runoff rate estimation. A more detailed description of the approaches follows.

Table 2: Average Remaining Loan Life by Asset Class

Loan Asset Class	**Runoff Rate Estimation Approach**	**Estimated Remaining Life of Loan Balance (Years)**[19]
Residential real estate (RRE)	Use average historical runoff at each horizon	4.91
Wholesale – Commercial real estate (CRE)	Constant runoff rate set to match average remaining contractual maturity; loan life truncated at eight years	3.58
Wholesale – Commercial & industrial, Other		2.91
Cards	Constant runoff over two years	1.00
Auto and Other retail	Constant runoff over six years	3.00

Source: Black Knight McDash and authors' calculations.

For residential real estate, we compute the average loan prepayment and maturation rate at each horizon for the portfolio of first mortgages using Black Knight McDash lender processing data from 1992 through 2018.[20] We use this as a loan runoff rate, but cap the remaining loan lifetime at 20 years.

For the commercial and industrial (C&I) and commercial real estate loans (CRE), we assign a constant runoff rate, and cap the remaining loan lifetime at eight years. We set the quarterly runoff rate to 5.25% for commercial real estate, and 6.75% for commercial and industrial to approximate the average remaining contractual maturity of such loans within loan-level regulatory data collections. This will overstate the life of loan balances to the extent that balances are repaid or amortized prior to maturity. We assign non-C&I, non-CRE wholesale loans the same remaining maturity distribution as C&I loans.

For auto loans, we assume that 1/6 of the initial portfolio runs off each year, with the balance reaching zero after six years. We use the prevalence of auto loans with six-year initial

[19] This statistic omits the additional impact of charge-offs on balance reduction.

[20] We first compute the average prepayment and maturation rate by quarter and horizon. Then, we take an equal weighted average across all quarters with data for the given horizon to create an average runoff rate by horizon. This runoff rate does not account for contractual amortization.

maturities to motivate this assumption. If a bank has constant sized portfolio of six-year auto loans, 1/6 of the balance will runoff each year ignoring prepayment and amortization.

Estimates of runoff rates of credit card and other open credit line balances require assumptions about the assignment of borrower cash flows to specific draws of credit.[21] Since CECL is not prescriptive here, we simply assume that 50% of the original credit card balance runs off over each of the first two years.

Overall, since most of our runoff rate estimates are calibrated using statistics that do not account for prepayment or contractual amortization, most of our estimates of loan life are likely a bit high. An exception is our estimate of a one-year average remaining credit card life, as some industry sources suggest average remaining lives may be as much as two years.

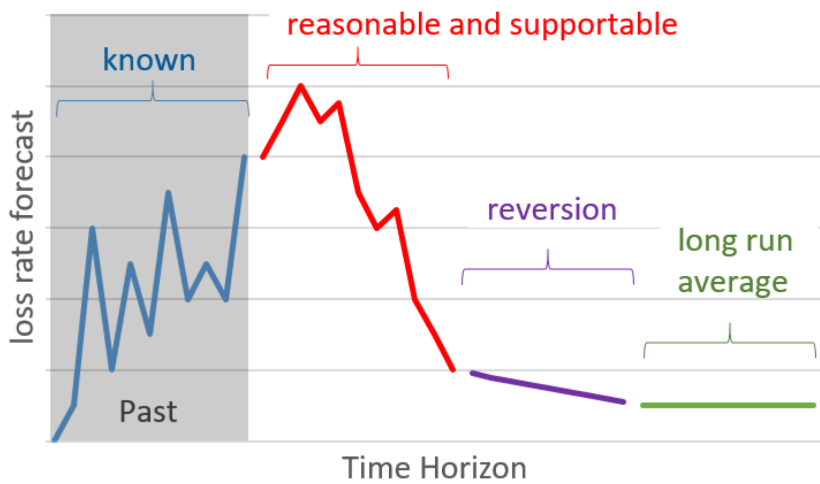
B. Portfolio Net Charge-off Rate Forecasts

Under CECL, the loss forecasting approach depends on the horizon.[22] Figure 2 provides an illustration. Banks are required to use their own loss forecasts over the near-term period in which the forecasts are considered "reasonable and supportable." On the other hand, long-run loss forecasts should be based on unadjusted historical loss information (e.g. long-run average loss rates). During the intervening period, loss forecasts should revert from the "reasonable and supportable" forecast to the long-run average. The CECL standard provides little guidance about how long each of these periods should be or about how banks should forecast near-term losses or revert them to the long-run average. CECL estimates can be quite sensitive to the loss forecasting approach (Chae et al. 2018 and Breeden 2018), so we follow an approach that allows for greater generality.

[21] Canals-Cerda (2019) provides a discussion of the significance of the allocation of cash flows when modeling the balance runoff of credit lines for CECL. He finds average life of credit card balances between 12 and 20 months, depending on the assignment of repayment cash flows.

[22] The full FASB standard discusses the development of credit loss estimates in 326-20-30 (p109-112): https://www.fasb.org/jsp/FASB/Document_C/DocumentPage?cid=1176168232528&acceptedDisclaimer=true

Figure 2: Loss Rate Forecast Overview



We do not construct a loss forecasting model to generate "reasonable and supportable" period forecasts. Instead, we develop three proxies for loss forecasts. These proxies represent the wide range of predictability associated with the various forecasting approaches that banks are likely to employ. However, construction of the forecast proxies requires the actual future losses. Therefore, when constructing proxies for forecasts with horizons as long as four-years, we cannot construct CECL allowances for the final four years of our data (2015-2018).

Our three proxies for loss forecasts address uncertainty about the amount of foresight in banks' CECL forecasts.[23] Our "low" and "high" foresight proxies represent lower and upper extremes to the amount of foresight that banks' "reasonable and supportable" CECL estimates might reflect. Our low foresight proxy simply sets the length of the "reasonable and supportable" forecasting horizon to zero, with the reversion to the long run average starting immediately. At the other extreme, the high foresight proxy is equal to the actual net charge-off rate throughout a four-year horizon, i.e. assumes four years of perfect foresight.[24] The four-year horizon is at least as long as the forecasting horizons that banks have indicated they might use in their CECL models.

[23] The amount of foresight incorporated in CECL models reflects both limits to the predictability of credit losses as well as the modelers' incentives to bias loss forecasts up or down.
[24] Since only about 1/3 of the initial loan portfolio remains on the balance sheet after four years, the high foresight approach is not quantitatively too different from a perfect foresight—at all horizons—approach.

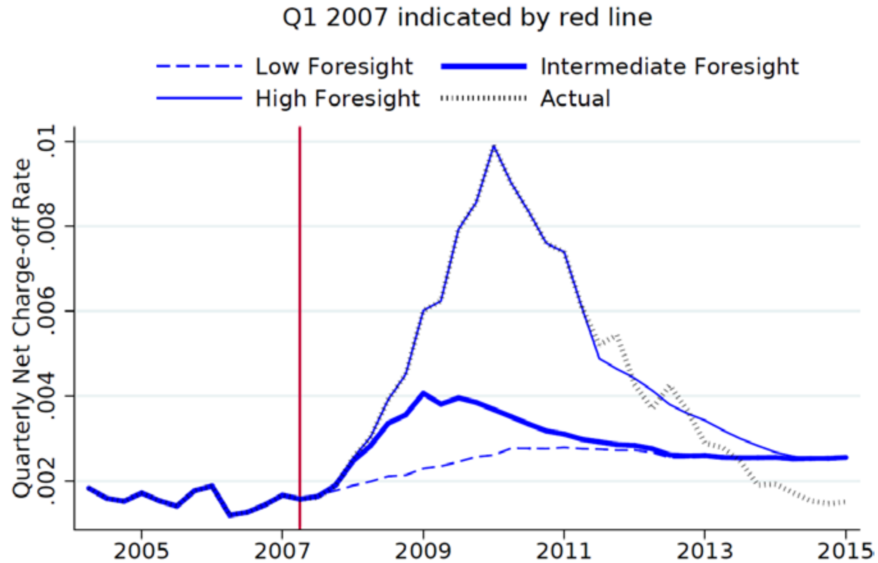
Our preferred "intermediate" foresight proxy incorporates information about credit losses at the same rate as the stock market. Accordingly, the "reasonable and supportable" forecasting horizon is set equal to the period over which banks' stock returns (partially) reflect changes in unexpected future net charge-offs—which we estimate at between 11 and 16 quarters, depending on the bank's size.[25] We believe that the intermediate foresight proxy comes closest to mimicking the amount of foresight that a reasonably sophisticated CECL model might capture. The quality of the intermediate foresight forecast is quite good over the first year, marginal in the second year, and poor beyond that. We discuss the construction of the intermediate foresight proxy in detail in Appendix B. This proxy uses stock return and market capitalization data from the Center for Research in Security Prices (CRSP).[26]

At the end of the "reasonable and supportable" horizon, we assume that banks' net charge-off forecasts follow a straight-line reversion to the long-run average forecast. We assume that the long-run average forecast equals the average net charge-off rate for the asset class in the full Y-9C data. Next, we set the length of the reversion period to minimize forecasting error, which results in a period of 10 to 12 quarters depending on the bank size.[27]

Figure 3 compares forecasts made in Q1 2007 under our three proxies. Differences between the low and high foresight proxy are extreme at that point in time, with high foresight fully anticipating the rise in loss rates and the other missing it almost entirely. Our preferred intermediate foresight proxy suggests that loss rate forecasts made in early 2007 would have foreseen net charge-off rates doubling over the following two years, but still peaking at only 40 percent of the level that losses actually reached in 2009.

[25] We classify bank holding company's size based on their share of aggregate assets in their fourth quarter of reporting in the FR Y-9C. Asset share breakpoints are set equal to those corresponding to $10, $50, and $250 billion in total assets as of Q2 2010.
[26] Center for Research in Security Prices, CRSP 1925 US Stock Database, Wharton Research Data Services, http://www.whartonwrds.com/datasets/crsp/. We link stock returns and market capitalization to BHC in our sample with use of the 2017 Federal Reserve Bank of New York's CRSP-FRB link, available at https://www.newyorkfed.org/research/banking_research/datasets.html.
[27] We choose the straight-line reversion length in order to minimize the sum of squared forecasting errors—weighted by lagged total assets—for quarterly net charge-off rates one to twenty quarters into the future.

Figure 3: Q1 2007 Forecasts of Net Charge-offs



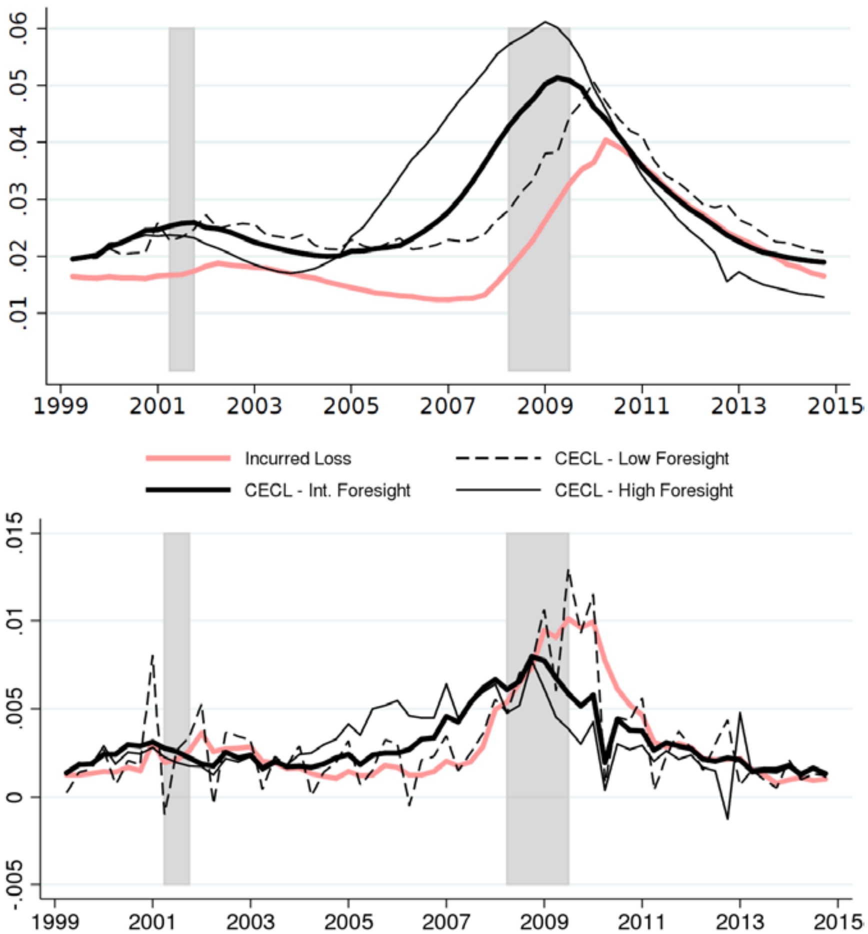
Source: Black Knight McDash, CRSP, FR Y9-C, NY FRB CRSP-FRB Link, and authors' calculations.

C. Comparison of Allowances under CECL and the ILM

We use Equation 1 to estimate CECL allowances (ACL) from our estimates of balance runoff rates and net charge-off rate forecasts. We plot the resulting aggregate ACL and provision expenses in the top and bottom panels of Figure 4.[28] The black curves in these figures represent our estimates under three CECL forecasts. For comparison purposes, the red curve provides the actual historical values under the ILM. All allowances and provision expenses are given as a share of aggregate loan balances. We estimate CECL allowances through the of 2014, as estimates under the intermediate and high foresight approaches require up to four years of future net charge-off data.

[28] Provision expenses in Figure 4 are derived under the assumption that the portfolio size is unaffected by CECL. We relax this assumption later. The volatility of provision expenses in the low foresight model are due to heavy dependence of net charge-off forecasts on the most recent actual level of net charge-offs, which can be volatile.

Figure 4: Aggregate U.S. BHC Allowances (Top) and Provision Expenses (Bottom) as a Fraction of Aggregate Loan Balances, by Quarter [29]



Note: Gray regions indicate NBER recessions.

Source: Black Knight McDash, CRSP, FR Y9-C, NBER, NY FRB CRSP-FRB Link, and authors' calculations.

Figure 4 shows that while allowance levels are typically only slightly higher under CECL during expansions, the peak level of allowances may be 100 to 200bp higher. This equates to a relatively modest average "day one" impact of CECL, unless the economy is in the early stages of a recession. Abad and Suarez (2018), Covas and Nelson (2018) and Fadil (2018) come to similar conclusions about CECL allowance levels. However, DeRitis and Zandi (2018) argue that when loss forecasts fully account for variation in origination credit quality, allowances may rise by *less* in a recession under CECL.

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[29] The volatility of provision expenses under the low foresight proxy is a result of the sensitivity of allowance levels to the most recent quarter's net charge-off rate.

The sharp increase in allowances that we find under CECL leading into the recession increases the pressure on banks to deleverage. However, the bottom panel shows that a disproportionate share of the associated provision expenses occurs prior to the recession under CECL, rather than during it. For example, roughly 62% of the trough to peak increase in allowances occurs prior to the recession in our "intermediate foresight" CECL estimate, in comparison to only 11% under the ILM.[30] We discuss the impact of this shift in provision expenses on lending in the next section.

IV. Impact on the Credit Cycle

In this section, we model the blue arrows in Figure 1—the impact of CECL-induced changes in capital ratios on the lending and capital distributions of U.S. bank holding companies.[31] With our framework complete, we assess the impact of CECL on credit cyclicality. Under a range of plausible bank responses to changes in capital, CECL appears slightly less procyclical than ILM. Specifically, CECL tends to slightly dampen lending when it is relatively high prior to recessions, and slightly increase lending when it is relatively low during recessions.

In our framework, CECL only affects lending through its impact on tier 1 risk-based capital ratios, *T1RBC*. As discussed in Section II, we assume that CECL does not change banks' target capital ratios. Therefore, in response to CECL, banks adjust their lending and distributions—dividends and net share purchases—proportionally to the standard's capital impact. Equations 2 and 3 below show how we model lending and distributions under CECL. Completing our model requires calibrating the adjustment speed parameters θ.

$$LoanGrowth_{bt}^{CECL} - LoanGrowth_{bt}^{Actual} = \theta_{bt}^{G}(T1RBC_{b,t-1}^{CECL} - T1RBC_{b,t-1}^{Actual}) \quad (2)$$

$$\frac{Distributions_{t}^{CECL}}{RWA_{t-1}^{CECL}} - \frac{Distributions_{t}^{Actual}}{RWA_{t-1}^{Actual}} = \theta_{bt}^{D}(T1RBC_{b,t-1}^{CECL} - T1RBC_{b,t-1}^{Actual}) \quad (3)$$

[30] This compares with approximately 43% of the allowance build occurring prior to the recession in Covas and Nelson (2018). However, their analysis assumes that this build in allowances does not result in any deleveraging prior to the recession.

[31] We measure lending by total loan balance. This is not a perfect measure of credit supply, as changes in loan balance also reflect charge-offs and transfers/sales of loans. However, adjusting lending growth for charge-offs does not affect our conclusions about CECL's impact on lending cyclicality.

We follow three approaches to calibration. In our baseline approach, we estimate a single value for each of θ^G and θ^D using a regression-based analysis of historical bank data. In our literature approach, we instead use a range of values for θ^G and θ^D inferred from studies of the impact of bank capital and capital requirements on lending. In our conditional approach, we recognize that adjustment speeds relate to bank leverage, and calibrate different values of θ for more and less leveraged banks.[32] We describe the baseline and literature based capital adjustment processes in more detail below, leaving the conditional approach to Appendix D, as it yields similar conclusions to our baseline approach.

Once we have θ^G and θ^D, we complete the model by specifying how the resulting changes in allowances and lending affect banks' net income. Since we assume that all bank assets scale proportionally, we also assume the impact on net interest income is proportional to the impact on lending. Similarly, we assume that CECL's impact on net interest expense is proportional to its impact on liabilities.[33] We use the historical average effective tax rate of 31% to convert pre-tax net income into capital. Appendix A presents the system of equations defining our model.

We estimate outcomes under CECL at the bank-level starting in the second quarter in which we have the necessary data in the Y-9C. In most cases, this is the second quarter of 1996.[34] In the initial observation of each bank, we assume banks have the same size and capital ratios under CECL as they had under the ILM. However, different provision expenses under CECL result in differences in the end of quarter capital. Differences in capital affect distributions and lending in the next quarter. The changes to capital distributions and lending—in addition to the different provisions under CECL—all contribute to differences in outcomes in subsequent quarters. We give the process six quarters to "burn in," and compare lending outcomes starting in 1998.

A. Capital Adjustment Processes

- *Baseline* – We use regressions to estimate the empirical relationship between banks' regulatory capital and their subsequent lending growth. Our data are from the Y-9C and

[32] Carlson et al. (2013) show how the response of lending to capital depends heavily on leverage, bank size, and economic conditions. Berger et al. (2008) document further heterogeneity in the speed at which bank capital is adjusted.

[33] We assume that CECL does not affect the average interest rate on loans or the average cost of funding liabilities.

[34] Banks present at the beginning of 1996 account for an average of 70% of the loan market share of Y-9C filers.

span Q1 1997 through the end of 2017.[35] Our specification is given in equations (4) and (5) below.

$$LoanGrowth_{bt} = \alpha_b^G + \beta^G LoanGrowth_{b,t-1} + \theta^G T1RBC_{b,t-1} + \varepsilon_{bt}^G \quad (4)$$

$$\frac{Distributions_{bt}}{RWA_{b,t-1}} = \alpha_b^D + \beta^D \frac{Distributions_{b,t-1}}{RWA_{b,t-2}} + \theta^D T1RBC_{b,t-1} + \varepsilon_{bt}^D \quad (5)$$

In these regressions, we constrain the relationship of capital and lending to be the same across banks. We relax this assumption in the conditional approach (Appendix D). However, we allow for persistence in growth and distributions by including lagged outcomes.[36] We also use bank fixed effects α_b to control for differences in average growth and capital policies across banks.

We estimate equations (4) and (5) using ordinary least squares using fixed effects, recognizing that two forms of bias could affect results. First, our estimates of θ are mechanically upwards biased to the extent that the independent variable, *T1RBC*, is persistent and contemporaneously correlated with our dependent variables (Stambaugh 1999).[37] We do not adjust for this bias, as our unadjusted estimates of θ are still low relative to (1) most of the estimates in the literature and (2) estimates using instrumental variables designed to address this source of bias.[38] Second, loan demand may represent a source of omitted variable bias. This bias is proportional to and the same sign as the correlation of loan demand and capital ratios. We considered using quarter fixed effects and book-to-market ratios to control for loan demand, but these controls had little effect on our estimates.

Our baseline estimate of θ^G is 0.21 with a standard error of 0.04, while our baseline estimate of θ^D is 0.032 with a standard error of 0.003. For a hypothetical bank with a 10% risk-based capital ratio, these parameters imply that a one percentage point increase in the tier 1 ratio would result in a 21bp increase in quarterly loan growth and an increase in distributions equal to 3.2bp of risk-weighted assets or 32bp of capital. The increase in

[35] Our data on loan growth are from a merger-adjusted version of the FR Y-9C. Risk-based capital ratios are unavailable in earlier periods. Our results are qualitatively similar using leverage ratios and a longer time-series.

[36] To maintain simplicity, equations (2) and (3) do not include lagged outcomes. The estimated β in equations (4) and (5) are close to zero, so the quantitative impact of including lags in (2) and (3) is minimal.

[37] In addition, our estimates may be affected by bias in estimates of coefficients on the lagged dependent variable β.

[38] Specifically, our OLS point estimate of $\theta^G = 0.21$ is lower than estimates of 0.25 to 0.35 obtained through the use of lagged levels as GMM instruments in first-differenced version of our specification (e.g. Arellano Bond 1991).

lending and capital distributions contribute roughly equally in pushing capital ratios back towards equilibrium. Our parameter choices imply that deviations from target capital have a roughly nine-quarter half-life.

- *Literature* – Many academic papers have studied the response of bank lending to changes in either capital or capital requirements. We summarize the empirical settings, approaches and findings from several of the papers in this literature in Appendix C. In many cases, expressing the results of these studies in comparable terms requires a bit of imputation. We use estimates of banks' capital adjustment processes from these papers as an alternative to our regressions.

  Many of the papers offer advantages relative to our regression approach. First, most of these papers study changes in capital requirements, and therefore their estimates do not reflect the impact of loss absorption on lending.[39] Second, many of these papers use quasi-experimental settings to identify effects of capital that are plausibly unrelated to loan demand.[40] However, the wide range of estimates from the literature also suggests that we should treat inferences about bank behavior in different settings with care.

  Table 3 below provides a range of estimated θ^G and θ^D from the set of academic papers we reviewed. Our estimate of the adjustment speed of lending is somewhat below the average, while our estimate of the adjustment speed of capital distributions roughly equals the median estimate from the literature. Many of the higher adjustment speeds found in the literature study periods of high financial stress, which may explain the higher adjustment speeds.

[39] To the extent that our regressions measure both the impact of capital requirements and loss absorption on lending, our "baseline" approach might overstate θ^G.

[40] Most of the papers study what they argue are either exogeneous changes to capital (e.g. Peek and Rosengren 1997) or capital requirements (e.g. Behn et al. 2016, Gropp et al. 2019). In addition, many use borrower level data to further control for borrower-specific credit demand. See Appendix C for more details.

Table 3: Comparison of Literature Based Bank Adjustment Parameters[41]

		Percentiles			Baseline
Statistic	Obs.	25th	Median	75th	(SE)
θ^{G}	16	0.31	0.44	0.73	0.21
					(0.04)
θ^{D}	5	0.009	0.032	0.120	0.032
					(0.003)

Source: FR Y9-C, literature review (see Appendix C), and authors' calculations.

We use this range of estimates to construct four calibrations of the capital adjustment process using the 25th and 75th percentile estimates of θ^{G} and θ^{D}, which can be read from Table 3: ($\theta^{G,25th}\theta^{D,25th}$), ($\theta^{G,25th}\theta^{D,75th}$), ($\theta^{G,75th}\theta^{D,25th}$) and ($\theta^{G,75th}\theta^{D,75th}$). In our analysis, we will consider the range of outcomes spanned by these four processes.

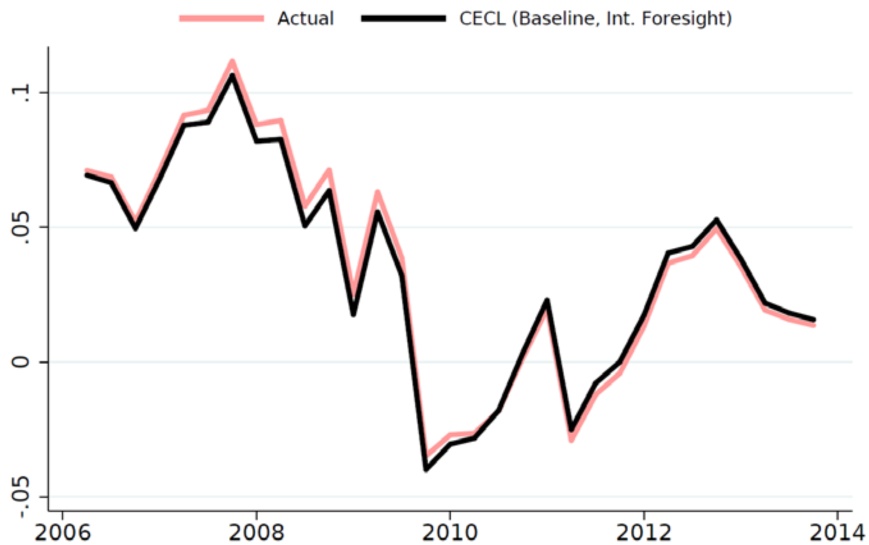
B. Lending Growth and Distributions Under CECL

Figure 5 illustrates our baseline estimate of the impact of CECL on bank lending over the period surrounding the Great Recession. The red curve represents actual annual aggregate lending growth under the ILM.[42] The black curve is our estimate of lending growth under CECL using our intermediate foresight CECL estimate and our baseline bank capital adjustment process.

[41] See Appendix C for the papers these statistics are derived from. To convert the annual impact in bp per 100bp change in T1 RBC (in Appendix C) to units comparable to our regressions, we multiply by 0.0025.

[42] This estimate is based on a merger-adjusted version of the Y-9C, and includes the set of holding companies included in our simulation. We look at annual lending growth to deal with seasonality.

Figure 5: Comparison of Year over Year Lending Growth



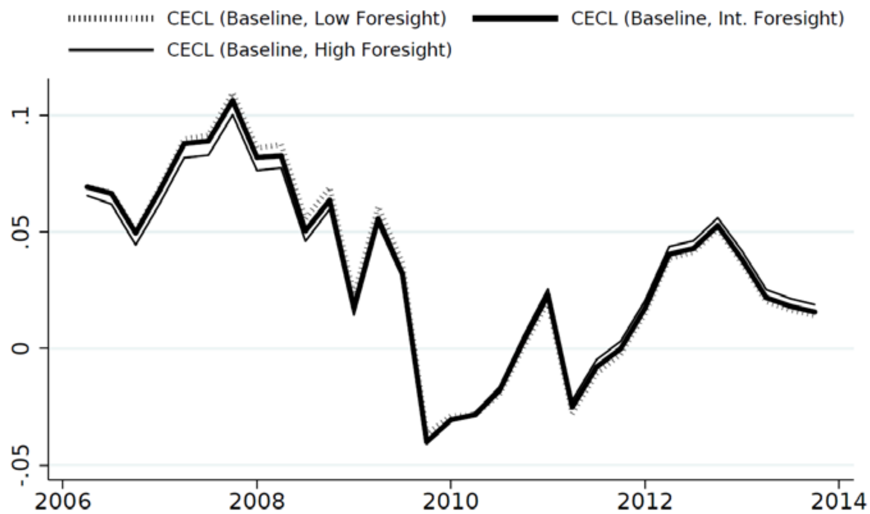
Source: Black Knight McDash, CRSP, FR Y9-C, NY FRB CRSP-FRB Link, and authors' calculations.

In our baseline model, CECL merely shifts net income and lending from the pre-2009 period—where lending growth is generally high—to the post-2009 period—where lending growth is generally low. Average lending growth in this model depends only on average loss rates, which we assume are unaffected. Similar to the impact on lending, we estimate that capital distributions under CECL would have been about six percent lower in the lead up to the crisis (2005 through 2007), and modestly higher thereafter. CECL has much less impact on lending and distributions over the period 1998 through 2006.

We measure the impact of CECL on the cyclicality of lending growth with two statistics. First, we look at the impact of CECL on the volatility of annual lending growth over the full estimation period (1998-2014). We find that this volatility declines from about 4.9 percent to 4.8 percent under CECL using our baseline capital adjustment approach. Second, we measure the impact of CECL on the magnitude of the largest peak-to-trough decline in lending around the Great Recession. This statistic is less generalizable, but focuses on a period in which additional lending may have had a larger positive impact on economic welfare. In our baseline approach, we estimate a decline in lending of 6.74% versus the largest actual decline of 6.54%. These two statistics suggest minimal—and opposite signed—effects of CECL on credit cyclicality under our baseline adjustment model.

Figure 6 summarizes how the foresight incorporated in CECL affects the standard's impact on lending. When foresight is greater, banks deleverage more and earlier prior to the downturn, resulting in a larger decline in lending growth earlier and larger increase in the recovery. As a result, lending growth volatility falls only half as much under the low foresight proxy and by twice as much under the high foresight proxy.

Figure 6: Year over Year Lending Growth Under CECL, Varying Foresight



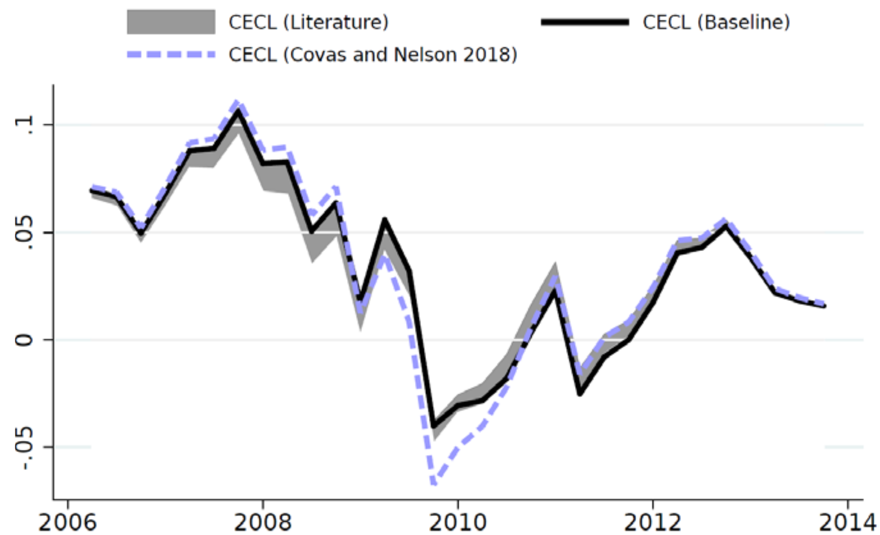
Source: Black Knight McDash, CRSP, FR Y9-C, NY FRB CRSP-FRB Link, and authors' calculations.

Figure 7 shows the variation in CECL impact that result under different capital adjustment processes. All curves in the figure make use of our intermediate foresight proxy for CECL allowances. The thick black curve is the same as in Figures 5 and 6, and represents our baseline adjustment process. The gray region represents the range of lending growth spanned by our four literature based calibrations of the adjustment process. Finally, the purple curve is our estimate under the capital adjustment process used in Covas and Nelson (2018). In this paper, lending responds to the capital impact of CECL starting in the fourth quarter of 2008, and capital distributions are unaffected.[43]

[43] Covas and Nelson (2018) estimate a 9% decline resulting from a 160bp reduction in capital ratios. While the response horizon is not given, the authors base this response on work by Behn et al. (2016). Behn et al. (2016) study lending of German IRB banks relative to standardized approach banks over an average difference in post and pre observation time of about six quarters. We therefore translate Covas and Nelson's model calibration into $\theta^G = \frac{9}{6*1.6} = 0.938$ after Q3 2008, and $\theta^G = 0$ otherwise.

Figure 7: Year over Year Lending Growth under CECL (Intermediate Foresight)

Sensitivity to Capital Adjustment Process



Note: The gray region represents lending growth suggested by our range of literature-based approaches.

Source: Black Knight McDash, Covas and Nelson (2018), CRSP, FR Y9-C, literature review (see Appendix C), NY FRB CRSP-FRB Link, and authors' calculations.

While the curves in Figure 7 show some variation, their basic shape is similar. Regardless of banks' response to the accounting change, loan loss accounting is not a primary driver of fluctuations in lending growth. The range of literature-based estimates of CECL impact generally suggests a stronger impact of CECL on lending growth. This results from our baseline approach's assumption of a lower speed of lending adjustment. The purple curve tracks actual lending growth—by construction—until the end of 2008. At the end of 2008, banks rapidly start to adjust in response to the larger accumulation of allowances under CECL, resulting in the substantial decline in lending from 2009 through 2011.[44]

Table 4 shows how our measures of lending cyclicality vary across the different capital adjustment processes. Our literature-based estimates generally suggest that CECL dampens cyclicality more than our baseline estimates do. Considering both approaches, we conclude that CECL is likely to be slightly less procyclical than ILM. In contrast to these findings, under the capital adjustment process implied by Covas and Nelson (2018), lending growth volatility increases and the peak-to-trough decline in lending is over 30% larger.

[44] Under this assumed capital adjustment process, greater foresight actually exacerbates lending cyclicality. Under the high foresight approach, the accumulation of allowances is greater, leading to a sharper reduction in lending at the end of 2008 and a 55% increase in the size of the peak-to-trough decline in lending.

Table 4: Impact of Capital Adjustment Process on Lending Cyclicality under CECL

	CECL Impact on Lending % (vs ILM)	
	Growth Volatility	Peak-to-Trough Decline
Capital adjustment process:	Intermediate foresight CECL	
Baseline	-1.5%	+3.1%
Literature [range]	-5.8% to -1.5%	-5.0% to +5.8%
Covas and Nelson (2018)	+3.0%	+33.5%

Note: Positive values indicate greater procyclicality than the historical ILM, and vice versa.

Source: same as Figure 7.

Overall, our results suggest that CECL's impact on credit cyclicality depends on the extent to which (i) CECL allowances reflect foresight of future losses and (ii) banks promptly address cyclical losses of capital.

V. Caveats

In this section, we discuss caveats to our conclusions, organized by their likely impact. Taken as a whole, these suggest that a more complete (and complex) assessment framework would most likely find further reductions in credit cyclicality under CECL.

A. Reasons CECL may be Reduce Cyclicality Further

Our analysis does not assess the impact of CECL on broader macroeconomic conditions. However, there are two reasons why the standard may reduce the frequency and severity of recessions, and thereby dampen credit cyclicality. Banks deleverage more in advance of stress periods under CECL, which may reduce the frequency of bank failures. Second, CECL may disproportionately increase the capital costs of lower credit quality originations (see DeRitis and Zandi 2018). If so, the standard may further reduce the buildup of credit that increases the vulnerability of the banking system to shocks.

Our net charge-off forecasts do not account for variation in lending standards over time. To the extent that variation in lending standards predict variation in lifetime credit losses, our favored "intermediate foresight" CECL model may understate the predictability of net charge-offs, resulting in lower pre-crisis level of loss allowances (e.g., see DeRitis and Zandi, 2018, for mortgage portfolios).

B. Reasons CECL may Increase Cyclicality

CECL has a relatively large impact on loan loss allowances at origination.[45] As a result, the standard could discourage lending at banks where capital constraints bind tightly in the short run. If lending is lower when banks are more capital constrained, then this is a procyclical feature of the standard that we do not account for.

C. *Reasons CECL may have Less Impact*

Within CCAR, allowances are set equal to the following four quarters of firms' projected loan losses.[46] As long as this remains the case, increased allowances are roughly offset by decreased stress period losses.[47] This may neutralize the impact of CECL on any banks for which stress tests are part of the binding capital requirements.

Banks have significant discretion in how they model CECL, and an incentive to do so in a way that minimizes the constraints on their economic decision-making. Since incurred loss allowances should also reflect these incentives, differences between allowances under CECL and ILM may be smaller than we suggest. This would reduce any impact of the standard.

Many of our estimates of banks' capital ratio adjustment process (i.e. θ^G and θ^D) rely on settings where the capital impact is permanent or persistent. In contrast, increases in allowances under CECL are short lived; CECL allowances are materially higher than under the ILM for about two to three years around a recession. Banks might adjust more slowly to such transitory capital impacts.

D. *Other Issues Potentially Affecting CECL's Impact on the Credit Cycle*

Our conclusions rely on time-series relationships between lending growth and charge-offs around the financial crisis. In our conclusions, we implicitly assume that these time-series relationships are likely to be similar around future recessions.

We apply the same loan balance runoff across the entire history for each asset class. Variation in runoff that corresponds with the state of the economy could affect our conclusions. For example, if the life of a loan falls when lending growth is low, CECL would dampen lending growth volatility further, and vice versa.

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[45] In particular, under the ILM, loss allowances at origination may be zero for portfolios where allowances are set in a loan-specific manner. For further discussion, see Ryan (2019).

[46] See documentation at https://www.federalreserve.gov/publications/files/2018-dfast-methodology-results-20180621.pdf

[47] The offset depends on the timing of losses in the stress scenario.

Certain CECL modeling assumptions could affect our estimates of the level of CECL ACL, but generally should not have much impact on the fluctuations in ACL or credit cyclicality. Specifically, our allowance estimates would be lower if (1) we accounted for prepayment and contractual amortization when modeling loan balances or (2) we discounted future net charge-offs. On the other hand, industry commentary as well as modeling work by Canals-Cerda (2019) suggests that the average life of credit card balances may be somewhat more than the one-year estimate that we use.

A. Issues Outside the Scope of our Paper

CECL may increase banks' operational costs, through requiring additional headcount, software and consulting services. The standard may result in greater production and sharing of information about credit market conditions. As suggested in Figure 4, CECL will likely increase aggregate loan loss allowances. The impact on allowances should vary significantly across loans and firms,[48] with larger increases associated with longer term and higher credit risk lending in particular, including credit cards.[49] As a result, pricing for such loans may increase, resulting in a shift towards shorter term lending.

VI. Conclusion

CECL results in earlier accumulation of allowances prior to recessions than the ILM. This feature of the standard encourages banks to deleverage and raise capital before credit conditions are at their tightest. However, CECL may also result in a larger accumulation of allowances around recessions, potentially encouraging banks to deleverage more. Accounting for both of these effects, we find that CECL would have reduced lending in the lead up to the financial crisis and increased it during the recovery, modestly decreasing the volatility of lending growth. These conclusions are robust to a range of assumptions about banks' foresight of losses and management of capital ratios.

[48] Analyst reports suggest CECL will have substantially different initial capital impact across banks (e.g. KBW February 15, 2019 report "Financial Stocks Weekly: Countdown to CECL" and Chart 48 of Autonomous April 4, 2019 report "Late Cycle Blues – Regional Edition").

[49] For example, in February 2019 JP Morgan Chase CFO Marianne Lake told investors that reserves on credit cards would roughly double. Also in February 2019, Mission Federal CFO Doug Wright stated to American Banker, "Longer-lived assets and those with proportionately lower credit quality are going to take a greater hit up front." Additionally, see Exhibits 1 and 2 of Moody's March 11, 2019 report, "CECL accounting will not materially affect most banks' underlying credit strength."

Our analysis may overstate the magnitude of CECL's impact to the extent that i) banks have significant discretion when modeling CECL ACL, ii) banks are indifferent to the shorter-term shifts between allowances and capital implied by CECL or iii) the capital impact at banks subject to CCAR is roughly offset by reductions in the modeled stress losses. On the other hand, our framework does not incorporate potential effects of CECL on the composition of bank lending and loan pricing, which DeRitis and Zandi (2018) suggest could further reduce cyclicality.

References

Abad, Jorge and Javier Suarez. (2018) "The Procyclicality of Expected Credit Loss Provisions." *CEPR Discussion Paper 13135*. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3244507

Agenor, Pierre-Richard and Roy Zilberman. (2015) "Loan Loss Provisioning Rules, Procyclicality, and Financial Volatility." *Journal of Banking and Finance*, v 61, 301-315.

Agenor, Pierre-Richard and Luiz Pereira da Silva. (2017) "Cyclically Adjusted Provisions and Financial Stability." *Journal of Financial Stability*, v 28, 143-162.

Aiyar, Shekhar, Charles Calomiris and Tomasz Wieladek. (2014) "Does Macro-Prudential Regulation Leak? Evidence from a UK Policy Experiment." *Journal of Money, Credit, and Banking*, v 46, no. 1, 181-214.

Arellano, Miguel and Stephen Bond. (1991) "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations." *Review of Economic Studies*, v 58, 277-297.

Bassett, William, Mary Beth Chosak, John Driscoll and Egon Zakrajsek. (2014) "Changes in Bank Lending Standards and the Macroeconomy" *Journal of Monetary Economics*, v 62, 23-40.

Beatty, Anne and Scott Liao. (2011) "Do Delays in Expected Loss Recognition Affect Banks' Willingness to Lend?" *Journal of Accounting and Economics*, v 52, 1-20.

Behn, Markus, Rainer Haselmann and Paul Wachtel. (2016) "Procyclical Capital Regulation and Lending." *The Journal of Finance*, v 71, no. 2, 919-956.

Berger, Allen, Robert DeYoung, Mark Flannery, David Lee and Ozde Oztekin. (2008) "How Do Large Banking Organizations Manage Their Capital Ratios?" *Journal of Financial Services Research*, v 34, 123-149.

Bernanke, Ben and Cara Lown. (1991) "The Credit Crunch." *Brookings Papers on Economic Activity*, v 2, 205-247.

Berrospide, Jose and Rochelle Edge. (2010) "The Effects of Bank Capital on Lending: What Do We Know, and What Does It Mean?" *International Journal of Central Banking*, v 6, no. 4, 5-54.

Bouvatier, Vincent and Laetitia Lepetit. (2012) "Provisioning Rules and Bank Lending: A Theoretical Model." *Journal of Financial Stability*, v 8, no. 1, 25-31.

Bridges, Jonathan, David Gregory, Mette Nielsen, Silvia Pezzini, Amar Radia and Marco Spaltro. (2014) "The Impact of Capital Requirements on Bank Lending." *Bank of England Working Paper No. 486*.

Breeden, Joseph. (2018) "CECL Procyclicality: It Depends on the Model." Working paper available at: https://www.prescientmodels.com/articles/CECL-Procyclicality.pdf

Bushman, Robert and Christopher Williams. (2012) "Accounting Discretion, Loan Loss Provisioning, and Discipline of Banks' Risk-Taking." *Journal of Accounting and Economics*, v 54, no. 1, 1-18.

Canals-Cerda, Jose. (2019) "From Incurred Loss to Current Expected Credit Loss (CECL): A Forensic Analysis of the Allowance for Loan Losses in Unconditionally Cancelable Credit Card Portfolios." *Federal Reserve Bank of Philadelphia Working Paper 19-08*. Available at: https://philadelphiafed.org/-/media/research-and-data/publications/working-papers/2019/wp19-08.pdf

Carlson, Mark, Hui Shan and Missaka Warusawitharana. (2013) "Capital Ratios and Bank Lending: A Matched Bank Approach." *Journal of Financial Intermediation*, v 22, 663-687.

Chae, Sarah, Robert Sarama, Cindy 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 Working Paper 020*. Available at: https://www.federalreserve.gov/econres/feds/files/2018020pap.pdf

Cohen, Benjamin and Gerald Edwards. (2017) "The New Era of Expected Credit Loss Provisioning." *BIS Quarterly Review*. March 2017 Available at: https://www.bis.org/publ/qtrpdf/r_qt1703f.pdf

Covas, Francisco and William Nelson. "Current Expected Credit Loss: Lessons from 2007-2009." (2018) *Banking Policy Institute Working Paper*. Available at: https://bpi.com/wp-content/uploads/2018/07/CECL_WP-2.pdf

Cummings, James and Kassim Durrani. "Effect of the Basel Accord Capital Requirements on th Loan-Loss Provisioning Practices of Australian Banks." (2016) *Journal of Banking and Finance*, v 67, 23-36.Du, Fang, Chris Finger, Ben Ranish and Robert Sarama. (2018) "Sources of Modelling Variation in CECL Allowances." *The New Impairment Model Under IFRS 9 and CECL*. Edited by Jing Zhang. Risk books.

DeRitis, Christian and Mark Zandi. (2018) "Gauging CECL Cyclicality." *Moody's Analytics Analysis Paper*. Available at: https://www.economy.com/mark-zandi/documents/2018-12-03-Gauging-CECL-Cyclicality.pdf

Fadil, Michael. (2018) "The Impacts of CECL: Empirical Assessments and Implications." *The New Impairment Model Under IFRS 9 and CECL*. Edited by Jing Zhang. Risk books.

Fraisse, Henri, Matthias Le and David Thesmar. (2017) "The Real Effects of Bank Capital Requirements." *European Systemic Risk Board Working Paper No. 47*.

Francis, William and Matthew Osborne. (2012) "Capital Requirements and Bank Behavior in the UK: Are there Lessons for International Capital Standards." *Journal of Banking and Finance*, v 36, 803-816.

Gambacorta, Leonardo and Paolo Emilio Mistrulli. (2004) "Does Bank Capital Affect Lending Behavior?" *Journal of Financial Intermediation*, v 13, 436-457.

Gambacorta, Leonardo and Hyun Song Shin. (2018) "Why Bank Capital Matters for Monetary Policy." *Journal of Financial Intermediation*, v 35, 17-29.

Gropp, Reint, Thomas Mosk, Steven Ongena and Carlo Wix. (2019) "Banks Response to Higher Capital Requirements: Evidence from a Quasi-Natural Experiment." *The Review of Financial Studies*, v 32, no. 1, 266-299.

Jimenez, Gabriel, Steven Ongena, Jose-Luis Peydro and Jesus Saurina. (2017) "Macroprudential Policy, Countercyclical Bank Capital Buffers, and Credit Supply: Evidence from the Spanish Dynamic Provisioning Experiments." *Journal of Political Economy*, v 125, no. 6, 2126-2177.
Memmel, Christoph and Peter Raupach. (2010) "How do Banks Adjust Their Capital Ratios?" *Journal of Financial Intermediation*, v 19, 509-528.
Noss, Joseph and Priscilla Toffano. (2016) "Estimating the Impact of Changes in Aggregate Bank Capital Requirements on Lending and Growth During an Upswing." *Journal of Banking and Finance*, v 62, 15-27.
Peek, Joe and Eric Rosengren. (1995) "Bank Regulation and the Credit Crunch." *Journal of Banking and Finance*, v 19, 679-692.
Peek, Joe and Eric Rosengren. (1997) "The International Transmission of Financial Shocks: The Case of Japan." *The American Economic Review*, v 87, no. 4, 495-505.
Peek, Joe and Eric Rosengren. (2000) "Collateral Damage: Effects of the Japanese Bank Crisis on Real Activity in the United States." *The American Economic Review*, v 90, no. 1, 30-45.
Ryan, Stephen. (2019) "The CECL Approach." *Banking Perspectives*, Q1. Available at: https://www.bankingperspectives.com/the-cecl-approach/.
Stambaugh, Robert. (1999) "Predictive regressions." *Journal of Financial Economics*, v 54, 375-421.

Appendices

Appendix A – CECL Impact Framework: System of Equations

In this appendix, we describe the system of equations that we use to estimate bank-level outcomes under CECL given *actual* outcomes under ILM, our estimates of allowances under CECL and our estimates of banks' capital adjustment processes θ^G and θ^D. Since the net charge-off rate is the same in our setup under both ILM and CECL, we do not denote it by ^{CECL} or ^{ILM}. For each bank, we assume that all variables, except for allowances, start at the same level under CECL and ILM.[50] From the second quarter onwards, differences in outcomes between the CECL and ILM regimes are driven by differences in the evolution of tier 1 risk-based capital ratios denoted by δ_t.

$$\delta_t = T1RBC_t^{CECL} - T1RBC_t^{ILM}$$

We model lending growth and capital distributions that respond proportionally to this difference in capital ratios (equations A.1 and A.2 below).[51] The calibration of θ^G and θ^D is described in Section IV.

[50] We start in the first quarter in which all necessary variables are present for the bank in the Y9C. For most banks, this is the second quarter of 1996.
[51] In the simulation we outline, assets are defined as gross of loan loss allowances (i.e. accounting assets plus loan loss allowances).

$$\Delta Ln(Loans)_t^{CECL} - \Delta Ln(Loans)_t^{ILM} = \theta^G \delta_{t-1} \text{ (A.1)}$$

$$\frac{Distributions_t^{CECL}}{RWA_{t-1}^{CECL}} - \frac{Distributions_t^{ILM}}{RWA_{t-1}^{ILM}} = \theta^D \delta_{t-1} \text{ (A.2)}$$

We estimate CECL allowances (ACL) under the approaches detailed in Section III. In our framework, with net charge-off rates the same under CECL, provisions expenses are given by equation (A.3).[52]

$$ProvisionExpense_t^{CECL} - ProvisionExpense_t^{ILM} = NCORate_t(Loans_{t-1}^{CECL} - Loans_{t-1}^{ILM}) + (\Delta ACL_t^{CECL} - \Delta ALLL_t^{ILM}) \text{ (A.3)}$$

We assume interest income and expenses are proportional to lagged assets and liabilities respectively (equations A.4 and A.5).

$$InterestIncome_t^{CECL} = InterestIncome_t^{ILM}\left(Assets_{t-1}^{CECL} \Big/ Assets_{t-1}^{ILM}\right) \text{ (A.4)}$$

$$InterestExpense_t^{CECL} = InterestExpense_t^{ILM}\left(Liabilities_{t-1}^{CECL} \Big/ Liabilities_{t-1}^{ILM}\right) \text{ (A.5)}$$

With the impact to the affected components of net income defined in (A.3) through (A.5), we calculate net income under CECL using equation (A.6). The parameter τ = 31% represents the long-run average effective tax rate in our sample.

$$NetIncome_t^{CECL} - NetIncome_t^{ILM} = (1-\tau)[(InterestIncome_t^{CECL} - InterestIncome_t^{ILM}) - (InterestExpense_t^{CECL} - InterestExpense_t^{ILM}) - (ProvisionExpense_t^{CECL} - ProvisionExpense_t^{ILM})] \text{ (A.6)}$$

Finally, the impact of CECL on net income and distributions flow through directly to capital, as shown in equation (A.7).

$$\Delta T1Capital_t^{CECL} - \Delta T1Capital_t^{ILM} = (NetIncome_t^{CECL} - NetIncome_t^{ILM}) - (Distributions_t^{CECL} - Distributions_t^{ILM}) \text{ (A.7)}$$

At this point, we calculate tier 1 capital ratios under CECL and δ_t, allowing us to estimate outcomes under CECL for quarter t+1.

Appendix B – The "Intermediate" Foresight Proxy for Net Charge-off Forecasts

In our intermediate foresight proxy, we assume that net charge-offs follow a time-series process that is known by the banks. In addition, we assume that banks have some ability to estimate the residual of this model. Specifically, we assume that, on average, banks learn about

[52] Under this formula, transfers and other adjustments to allowances are unchanged under CECL.

the residual as quickly as it is reflected in the banks' equity market capitalization. Under assumptions detailed below, the covariances of banks' stock returns and subsequent net charge-off residuals serve to identify the average amount of advance knowledge banks had about those residuals. Note that this calibration relies heavily on the financial crisis for guidance on the amount of foresight we will have leading into the next downturn.

We start by specifying and estimating an autoregressive time-series model of the bank's net charge-offs, indicated by Equation (A.8) below.[53] We estimate this model using fixed effects to estimate the intercepts, and Bayesian Information Criterion to select the number of lags.[54] Net charge-off rates are significantly persistent; the loan-weighted time-series R-squared averages around 0.43.

$$NCO_{bt} = \alpha_b + A(L)NCO_{bt} + \varepsilon_{bt} \; (A.8)$$

We assume banks learn about their residual ε_{bt} over quarters *t-N* through *t*, and denote the information learned *k* periods in advance by $I_{b,t-k,t} = E_{b,t-k}[\varepsilon_{bt}] - E_{b,t-k-1}[\varepsilon_{bt}]$. Assuming the information *I* has a Gaussian distribution, estimating the banks' *k*-quarters in advance forecast is a classic signal extraction problem with the solution given in Equation (A.9) below.

$$E\left[E_{b,t-k}[\varepsilon_{bt}]\middle|\varepsilon_{bt}\right] = \frac{\sigma^2(\sum_{\tau=k}^{N} I_{b,t-\tau,t})}{\sigma^2(\varepsilon_{bt})}\varepsilon_{bt} = \frac{\sum_{\tau=k}^{N}\sigma^2(I_{b,t-\tau,t})}{\sum_{\tau=0}^{N}\sigma^2(I_{b,t-\tau,t})}\varepsilon_{bt} \; (A.9)$$

Next, we assume that every unit of *I* is associated with an unexpected decline in bank market equity of β < 0.[55] This assumption allows us to identify the variance of $I_{b,t-k,t}$ through the covariance of unexpected returns and residuals as shown in equation (A.10) below.

$$\begin{aligned}\sigma(R_{b,t-k}, \varepsilon_{bt}) &= \sigma\left(\beta \sum_{\tau=0}^{N} I_{b,t-k,t-k+\tau}, \sum_{\tau'=0}^{N} I_{b,t-\tau',t}\right) \\ &= \beta\sigma\left(\sum_{\tau=0}^{N} I_{b,t-k,t-k+\tau}, I_{b,t-k,t}\right) \\ &= \beta\sigma^2\left(I_{b,t-k,t}\right) \; (A.10)\end{aligned}$$

[53] All models in this section are estimated separately across banks in the different size categories noted in footnote 25.
[54] We estimate the number of lags at one or two depending on bank size. Our estimated model coefficients are fairly similar (and our resulting forecasts almost identical) when we instead estimate the autoregressive model using GMM IV methods developed to handle dynamic panel estimation (e.g. Arellano Bond).
[55] We might expect β < -1, as each dollar of residual net charge-off predicts further net charge-offs in subsequent quarters. The estimate of β is also affected by the possible correlation of information about future net charge-offs and other information relevant to banks' market value. This does not pose a challenge to identification as long as the same β applies to information received about net charge-offs at different horizons, i.e. the correlation of information about net charge-off residuals in *k* quarters and other value relevant information is independent of *k*. Discounting provides some justification for a smaller β at longer horizons, but has only a marginal impact on β.

The second line of the equation follows as information has zero serial correlation by construction, i.e. $\sigma\left(I_{b,t-k,t+j}, I_{b,t-\tau,t}\right) = 0$ if $k \neq \tau$. The third line follows from the fact that if residuals are not serially correlated, and all correlations $\rho(I_{b,t-\tau,t}, I_{b,t-\tau,t+k})$ have the same sign, then $\rho\left(I_{b,t-\tau,t}, I_{b,t-\tau,t+k}\right) = 0$ for all τ and k. We substitute equation (A.10) into (A.9), resulting in our "intermediate foresight" forecast given in equation (A.11) below. We estimate these forecasts, $E_{b,t-k}^{int}$, using data on 980 bank holding companies matched between the Center for Research in Security Prices (CRSP) and the FR Y-9C over the period Q2 1986 through Q4 2017.[56]

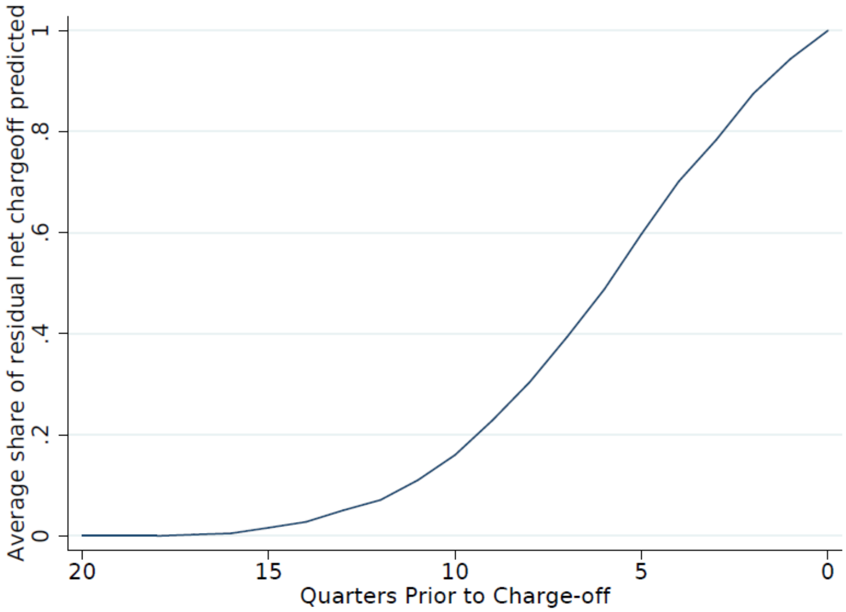
$$E_{b,t-k}^{int}[NCO_{bt}] = \widehat{\alpha_b} + E_{b,t-k}^{int}[\hat{A}(L)NCO_{bt}] + \frac{\sum_{\tau=k}^{N} \sigma\left(R_{b,t-\tau}, \varepsilon_{bt}\right)}{\sum_{\tau=0}^{N} \sigma\left(R_{b,t-\tau}, \varepsilon_{bt}\right)} \varepsilon_{bt} \quad (A.11)$$

Figure 8 shows the share of the net charge-off residual that is predicted by the bank at each horizon, i.e. $\frac{\sum_{\tau=k}^{N} \sigma\left(R_{b,t-\tau}, \varepsilon_{bt}\right)}{\sum_{\tau=0}^{N} \sigma\left(R_{b,t-\tau}, \varepsilon_{bt}\right)}$.[57] The slope of the curve represents the rate of learning about the residual, i.e. is proportional to $\sigma^2(I_{b,t-\tau,t})$. Our calibration implies that banks start to learn about their future net charge-offs around 15 quarters in advance. However, most of the information about net charge-offs is learned between two quarters and two years in advance.

[56] We use the CRSP-FRB linking dataset provided by the Federal Reserve Bank of New York: https://www.newyorkfed.org/research/banking_research/datasets.html. Our estimates are weighted by total assets. We verify that our calibration yields broadly similar, but noisier, results when equally weighting banks, using only non-crisis periods (the calibration relies heavily on the lead-lag relationship of stock returns and net charge-offs during the financial crisis), or after applying time fixed effects to net charge-offs. We assume expected returns are constant, but this makes little difference to the resulting calibration, as risk models explain relatively little of the variation in realized returns.

[57] Since we calibrate the approach separately for banks in different size categories, this figure represents a loan-weighted average calibration across all banks.

Figure 8: Average Share of Net Charge-off Residual Predicted by Horizon



Source: CRSP, FR Y9-C, NY FRB CRSP-FRB Link, and authors' calculations.

Appendix C –Literature on the Impact of Bank Capital on Lending and Distributions

The table below summarizes the studies we use in our literature-based bank capital adjustment process. Conversions are required to express some estimates in terms of the given units. First, based on the average risk-weight in the latest cross-section of our sample, we equate a 100bp change in risk-based capital buffer with a 65.8bp change in capital charge or simple leverage ratio. Second, we adjust estimates to account for variation in the horizon over which the studies measure impact. In studies with a pre- and post-treatment observation, we divide the impact by the average post minus pre-treatment horizon (in years). In papers providing long-term impacts of capital on lending, we divide results by three to reflect the typical share of the long-term impact occurring in the first year. Finally, we take estimates of the impact at the bank level—several papers measure the impact on lending at multiple levels (e.g. loan, bank, or borrower). Due to the ability to substitute lending across loans or banks, the measured impacts are generally smaller at the borrower level. In addition, for several papers we approximate the impact on annual distributions d from the impact on lending g, annual reversion of capital ratios to target r, and a baseline capital ratio of k=0.1, as d=100*r – k*g.

Paper	Empirical Setting	Source of Variation	Experimental Treatment	Implied Change per 100bp RBC: Aggregate Annual Lending (bp)	Implied Change per 100bp RBC: Annual Distributions / RWA (bp)
Our Baseline Approach Regressions				140	13.6
Gropp, Mosk, Ongena and Wix (2019)	Large EU banks (2009-2013)	Change in capital requirements (persistent)	Size-based capital requirements	133	0[58]
Gambacorta and Shin (2018)	Large G10 banks (1994-2012)	Capital		39	
Jimenez, Ongena, Peydro and Saurina (2017)	Spanish banks (1998-2013)	Change in provisioning (temporary)	Supervisory release of dynamic provisions	197[59]	
Fraisse, Le and Thesmar (2017)	Largest six French banks (2008-2011)	Change in capital requirements (persistent)	Variation in modeled risk weights[60]	133	
Behn, Haselmann and Wachtel (2016)	German banks (2008-2011)	Change in capital requirements (temporary)	Exposure to banks with cyclical (AIRB) capital requirements	263	
Noss and Toffano (2016)	UK banks (1986-2010)	Change in capital requirements (persistent)		350[61]	
Aiyar, Calomiris and Wieladek (2014)	UK banks (1998-2008)	Change in capital requirements (temporary)	Changes in bank-specific supervisory capital requirements	228[62]	
Bridges, Gregory, Nielsen, Pezzini, Radia and Spaltro (2014)	UK banks (1990-2011)	Change in capital requirements (temporary)	Changes in bank-specific supervisory capital requirements	335	7.5

[58] Authors find similar equity issuance and change in capital for treated and untreated banks.
[59] Authors find a smaller impact in benign periods.
[60] Setup assumes that variation in a borrower's AIRB credit risk weights across banks does not reflect a bank-borrower specific willingness to lend.
[61] Estimate is extrapolated from Chart 5.
[62] Uses the average of authors' long run reduction estimates of 5.7% and 8%.

Carlson, Shan and Warusawitharana (2013)	Smaller US banks (2001-2011)	Capital ratios		12[63]	
Francis and Osborne (2012)	Roughly 250 UK banks (1996-2007)	Capital buffers		120	36
Berrospide and Edge (2010)	US BHC (1992-2009)	Capital ratios		186[64]	12.8
Memmel and Raupach (2010)	80 large German banks (1998-2006)	Capital buffers		300[65]	60
Gambacorta and Mistrulli (2004)	Italian banks (1992-2001)	Capital buffers		136	
Peek and Rosengren (1997)	US branches of Japanese banks (1989-1995)	Capital ratios	Variation in parent exposure to losses in Japanese real estate	400	
Peek and Rosengren (1995)	New England (US) banks (1989-1992)	Capital ratios		42	
Bernanke and Lown (1991)	US (NJ) banks (1989-1991)	Capital ratios		164	

Appendix D – Calibration of the "Conditional" Capital Adjustment Process

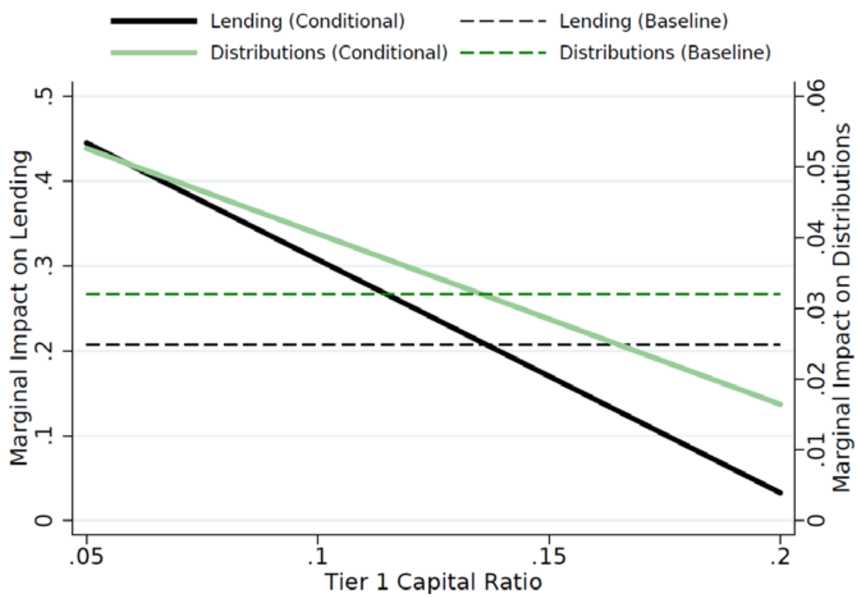
Our baseline and literature approaches assume that all banks adjust lending and distributions in response to changes in capital at the same speed. However, we might expect the adjustment speed θ to decline as a bank's capital ratio increases. At lower capital ratios, a larger adjustment to lending is required to change capital ratios by a given number of basis points and low capital banks may be under more pressure to deleverage quickly. At higher capital ratios, banks are not clearly trying to maintain a target buffer above regulatory capital requirements. They may be targeting economic loss absorption instead—and transfers between allowances and capital have no direct effect on loss absorption. As a result, the impact of CECL could be amplified when capital is lower or muted when capital is higher.

We make lending and distribution adjustment speeds conditional on capital by replacing θ^G and θ^D in equations (4) and (5) with $\theta_0^G + \theta_1^G T1RBC_{b,t-1}$ and $\theta_0^D + \theta_1^D T1RBC_{b,t-1}$. As expected, we find significant and positive θ_0 and significant and negative θ_1. In Figure 9, we

[63] Authors estimate an average impact of 100bp change in the capital ratio at an average of 12bp over 2006-2011, which are the years of greatest relevance in our study.
[64] Authors estimate loans increase $1.86 for every dollar of extra capital, and a quarterly autoregressive coefficient on capital ratios of 0.91 (extrapolation assumes a risk-based capital ratio of 10%).
[65] Estimate is based on the finding of an 18% adjustment towards target per month, with about 2/3 of the total adjustment operating through the liabilities (as opposed to assets).

compare the marginal impact of capital that results from this specification ($\theta_0 + 2 * \theta_1 T1RBC$) with our baseline results. Our conditional model finds faster adjustments than our baseline model when tier 1 capital ratios are below roughly 13%. We floor the marginal impacts at zero, as otherwise they become negative at high capital ratios.

Figure 9: Marginal Impact of Capital on Lending and Distributions



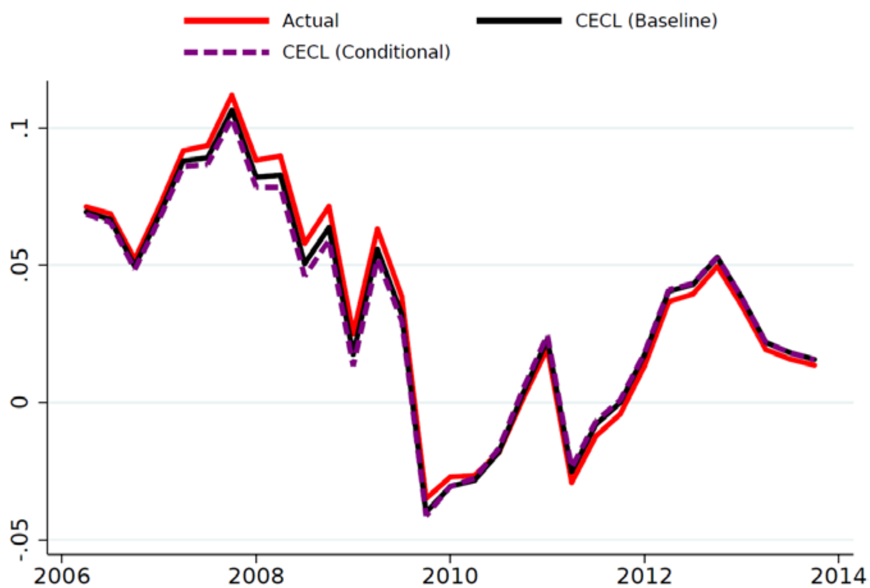
Source: FR Y9-C and authors' calculations.

In Figure 10, we compare our estimates of lending growth under the conditional approach (blue curve) with our baseline approach (black curve). Both estimates use our intermediate foresight estimates of CECL allowances. Since capital ratios are lower prior to recapitalization programs in 2009, the conditional approach yields more substantial reductions in lending than the baseline approach prior to the crisis, and less substantial increases in lending following.[66] However, both the conditional and baseline adjustment processes yield similar impacts of CECL on the volatility of lending growth (-2.1% conditional vs -1.5% baseline) and magnitude of the largest decline in lending (+2.5% conditional vs +3.1% baseline).

[66] In the conditional adjustment process, long run average lending growth depends on the correlation of CECL's capital impact and capital ratios. For example, if CECL tended to tighten capital when it is low (large negative effect on lending) and loosen capital when it was high (small positive effect on lending), then average lending growth rates would be lower.

Figure 10: Year over Year over Year Lending Growth under CECL (Intermediate Foresight)

Baseline vs Conditional Adjustment Process



Source: Black Knight McDash, CRSP, FR Y9-C, NY FRB CRSP-FRB Link, and authors' calculations.