THE EFFECT OF THE CURRENT EXPECTED CREDIT LOSS MODEL ON BANKS' LOAN LOSS RECOGNITION TIMELINESS

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2022

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A thesis submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy

March 2022

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Abstract

The switch from the incurred credit loss (ICL) to the current expected credit loss (CECL) model is a momentous change in bank accounting in the U.S. that aims to improve banks' loan loss recognition timeliness. In this paper, we examine whether the switch achieves the intended objective. Using novel hand-collected data on CECL adoption by public U.S. banks, we find that banks that voluntarily adopt the CECL model during the COVID-19 pandemic improve their loan loss recognition timeliness. This effect is more pronounced for riskier banks or banks with a higher proportion of loans individually evaluated for impairment, suggesting that eliminating the ICL's post-lending "trigger event" requirement for recording loan losses enhances banks' loan loss recognition timeliness. The effect also is more pronounced for banks that use the CECL transition provision to mitigate concerns about inadequate regulatory capital after recognizing additional loan losses. In addition, we document that CECL-adopting banks make a larger day-one adjustment to their loan loss allowance if, under the ICL regime, their loan loss recognition was less timely, consistent with these banks experiencing a larger catch-up effect in their loan loss allowance at the start of CECL adoption. Finally, we find that CECL-adopting banks reduce their lending, possibly due to concerns about having to record large expected loan losses during the COVID-19 pandemic. Overall, our study offers new insights into how the switch to a more forward-looking credit loss model affects banks' accounting practices.

Acknowledgements

First of all, I would like to express my sincere gratitude and appreciation to my chief supervisor Prof. Jeffrey Ng for his continuous guidance for my research and study. He always helps me to plan the research project, communicates with me about the progress of research projects and provides timely feedback regarding my written work and questions. I have learnt a lot of research and life wisdom from him, the most precious one of which is: to accept and face the reality. When I first started doing research, I was always frustrated when my paper was rejected or the empirical results didn’t support my hypothesis, and I wasn’t even motivated to continue doing research. But every time I talked with him, he taught me to face reality objectively: while it is difficult to publish a paper in a top-tier journal, what we should do is to learn from the failures and keep polishing our own works.

Second, I would like to express my gratitude to all professors, administrative staff and research students in AF for their sincere help. Being in AF always gives me great peace of mind knowing they are always there to help me when I am in trouble. I am grateful to my co-authors for their efforts in working on our papers and their encouragement and help in my studies and research.

Last but not least, I would like to express my sincere gratitude to my friends, who always stand behind me and give me support and encouragement. I would like to sincerely thank my parents. They always encourage me to pursue my career and give me the greatest tolerance, encouragement and love. Their love motivates me to strive forward.

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1. Introduction

Banks' financial reporting and disclosure practices play critical roles in the financial system and in the economy as a whole (Acharya and Ryan, 2016; Bushman, 2016). The single largest accrual item in bank accounting is loan loss provision, which reflects banks' loan loss estimates (Beatty and Liao, 2014). Timely loan loss recognition enables banks to build countercyclical regulatory capital reserves during expansionary periods, which can then serve as a cushion during periods of recessions. Timely loan loss recognition also enhances banks' risk management and reduces their vulnerability to liquidity and downside tail risk, thus enhancing banking system stability and dampening fluctuations in the real economy (Bushman and Williams, 2012, 2015).

Despite the benefits of timely loan loss recognition, the incurred credit loss (ICL) model, which has been used for many years in the U.S., constrains the timely recognition of banks' loan losses. Both regulators and financial statement users widely criticize this restriction for exacerbating banks' procyclicality (e.g., Financial Crisis Advisory Group, 2009; Beatty and Liao, 2011, 2021; International Monetary Fund, 2014; Bischof et al., 2021; Wheeler, 2021). In response, the Financial Accounting Standards Board introduced the current expected credit loss (CECL) model in 2016. The CECL model allows banks to estimate expected credit losses over the contract life of the financial instrument by incorporating forward-looking information. Bankers view the switch from the ICL to the CECL model as "the most sweeping change to bank accounting ever."[1]

In light of this significant accounting change, we examine whether the switch from the ICL to CECL model improves banks' loan loss recognition timeliness. To the best of our knowledge, few empirical studies have investigated this issue. The U.S. banking industry

[1] See American Bankers Association: Current Expected Credit Loss Standards (CECL), Compliance and Operational Challenges with the Current Expected Credit Loss Standard, available at https://www.aba.com/advocacy/our-issues/cecl-implementation-challenges.

provides a unique setting for doing so. Originally, the CECL model was scheduled for mandatory adoption by public banks in 2020. Due to the COVID-19 pandemic, the original schedule was delayed, although some banks voluntarily adopted the CECL model at different times starting in the first quarter of 2020. The staggered adoption enables us to draw inferences from difference-in-differences analyses.

We argue that whether the adoption of the CECL model actually improves banks' loan loss recognition timeliness is an empirical question. Compared to the ICL model, the CECL model has no "trigger event" restriction whereby the recognition of loan losses requires evidence that the borrower is likely to default. Without this requirement, banks' loan loss provisions can better reflect future deterioration in the loan portfolios. The CECL model also requires banks to incorporate forward-looking information, allowing them to estimate future loan losses that are expected to be realized in different macroeconomic scenarios. For example, banks can build up provisions during periods of expansion in preparation for losses sustained during recessions (Abad and Suarez, 2018; Buesa et al., 2020). Following this argumentation, we expect the switch to the CECL model to improve banks' loan loss recognition timeliness.

This improvement in loan loss recognition timeliness requires effective implementation. Adopting CECL during the COVID-19 pandemic creates unprecedented challenges for banks because in addition to the significant resources required to develop platforms to support the CECL production process, they must estimate the pandemic's effects on the economy and borrowers' creditworthiness. The regulatory forbearance during the pandemic and the inherent complexity in estimating future loan losses also affect banks' implementations of the CECL model. For example, the difficult conditions created by the COVID-19 pandemic might incentivize managers to rely on the latitude provided by the CECL model to opportunistically delay loan loss recognition.

To empirically test the effect of the switch to the CECL model on loan loss recognition timeliness, we construct a bank-quarter panel dataset that covers all public U.S. banks from the fourth quarter of 2018 to the first quarter of 2021. We manually collect data on banks' adoption of the CECL model by reading their 10-K or 10-Q filings. Banks that adopt during our sample period are voluntary adopters, and these adoptions occur in different fiscal quarters within the sample period. Using a difference-in-differences regression model, we find evidence that their loan loss recognition timeliness improves after CECL adoption, relative to non-adopting banks. The results of the parallel trend test show that adopters and nonadopters share similar loan loss recognition timeliness prior to adoption.

Next, we conduct several robustness tests for our main finding. First, we re-estimate our model using alternative indicators of expected loan losses; our inference that the CECL model positively affects loan loss recognition timeliness remains unchanged. Second, we show that our results are robust to several alternative samples. Third, we use the test developed by Oster (2019) to evaluate the sensitivity of our results to omitted variables. The coefficient of proportionality (δ) is substantially larger than 1, making it is unlikely that omitted variables explain the effect of switching to the CECL model on loan loss recognition timeliness. Finally, we perform a placebo test and find that loan loss recognition timeliness does not improve for pseudo adopters, suggesting that simultaneous confounding events do not shape our results.

We then perform two cross-sectional tests to study variations in the effect of CECL model adoption and to identify the channel through which the CECL model affects loan loss recognition timeliness. First, we predict and find that the post-CECL improvement in loan loss recognition timeliness is more pronounced for riskier banks or banks with a high proportion of loans individually evaluated for impairment. Considering that these banks would be more constrained in recognizing loan losses under the ICL model's trigger event requirement, this result indicates that removal of that threshold is one way the CECL model improves loan loss recognition timeliness. Second, we find that switching to the CECL model decreases banks' regulatory capital and the decrease is mitigated for banks that use the CECL transition provision allowing them to phase in the CECL's adverse effects on regulatory capital over three years. We also find that the effect of the CECL model on loan loss recognition timeliness is stronger for banks that use the CECL transition provision because the provision decreases concerns about capital inadequacy. Based on banks' pre-adoption regulatory capital ratio, we further split CECL adopters into two categories: high vs. low capital banks. Among low capital banks, the effect of the CECL model on loan loss recognition timeliness is notable only for banks that use the CECL transition provision, whereas the use of the provision does not change loan loss recognition timeliness among high capital banks. These results suggest that banks use the provisions to alleviate the negative effect of CECL model adoption on regulatory capital and that the CECL model can improve loan loss recognition timeliness more when banks are less concerned about regulatory capital inadequacy.

Finally, we conduct two supplementary tests. First, we explore the effect of a bank's pre-adoption loan loss recognition timeliness on its day-one adjustment to the loan loss allowance upon adopting the CECL model. We find that banks with less timely loan loss recognition under the ICL regime make a larger day-one adjustment, consistent with these banks experiencing a large catch-up in loan loss allowance at the start of CECL adoption. Second, we explore a real effect of the bank accounting change by examining how the CECL model affects bank lending. Improved transparency after adopting the CECL model might enable banks to obtain more financing from investors and depositors, which would in turn enable them to increase lending. Alternatively, adverse impacts on regulatory capital and earnings and the increased cost of risk management might reduce banks' willingness to lend. Consistent with the latter argument, we find that banks reduce lending after switching to CECL during the pandemic.

Our paper makes contributions from two important perspectives. Our paper makes contributions from two important perspectives. First, this paper offers both practitioners and regulators a better understanding of an important consequence of the CECL model, banks' loan loss recognition timeliness. The CECL model has been described as the most significant change ever to bank accounting and its adoption was changed from mandatory to voluntary due to the COVID-19 pandemic. Recent research highlights the importance of high-quality disclosure, especially when outsiders face difficulties in assessing firm prospects in times of macroeconomic difficulties (Nagar et al., 2019; Maslar et al., 2021). Hence, one might regard CECL adoption to enhance bank's disclosure quality via more timely loan loss recognition to be importance to the banks' various stakeholders, including regulators. However, the pandemic clearly makes it difficult for banks to accurately estimate loan losses. Moreover, incentives underlying reporting during the pandemic might alter the effectiveness of the CECL model because even without the trigger event requirement, banks might be unwilling to recognize loan losses in a timely way because of concerns about significant declines in profitability and capitalization. Our finding that CECL adoption enhances loan loss recognition timeliness suggests that banks are using the CECL model to improve their disclosure. Our finding that that regulatory actions are effective in facilitating the implementation of the CECL model insight highlights the importance of regulatory actions in facilitating implementation of accounting standards, especially when macroeconomic difficulties lead to real economic problems for entities implementing the standards. Overall, we believe that our study has the potential to inform practitioners, regulators and even the U.S. Congress about a momentous change in bank accounting standards.

Second, our paper also contributes to the literature on the determinants of loan loss recognition timeliness by offering further insight into how it is affected by credit loss provisioning models. Evidence in the literature indicates that banks' loan loss recognition timeliness depends on many factors, such as characteristics of its executives and directors (Ahmed et al., 2019; Sarkar et al., 2019), competition in the banking industry (Bushman et al., 2016), information sharing among banks (Balakrishnan and Ertan, 2021), strictness of external monitoring (Choi, 2018; Delis et al., 2018; Nicoletti, 2018; Balakrishnan et al., 2021), national culture (Kanagaretnam et al., 2014), and the tax system (Andries et al., 2017). Extending the recent research on the effects of credit loss provision models (e.g., Ertan, 2021; López-Espinosa et al., 2021; Kim et al., 2021), our paper confirms that the CECL model, as a forward-looking credit loss provision model, achieves the regulatory objective of more timely loan loss recognition, despite the concern that the considerable discretionary latitude allowed by the model might lead to less timely loan loss recognition. However, one of our supplementary analysis suggests that the more timely loan loss recognition comes at a possible cost of reduced lending.[2]

[2] One empirical advantage of using the U.S. setting, as opposed to an international setting, to study the effects of forward-looking credit loss provision models is the homogeneity in political and economic conditions within a country, which can mitigate endogeneity concerns.

2. Institutional background and hypothesis development

2.1. Switching from the incurred to the current expected credit loss model

Under the ICL model, banks recognize credit losses only if a trigger event shows that the borrowers are likely to default. Financial statement users have criticized this backward-looking method for generating "too little, too late" loss recognition and impairing the decision-usefulness of banks' financial statements. During the 2008 financial crisis, delayed loan loss provisions under the ICL model exacerbated procyclicality and thus amplified economic cycle fluctuations and jeopardized financial stability (Financial Crisis Advisory Group, 2009; Beatty and Liao, 2011; International Monetary Fund, 2014; Acharya and Ryan, 2016).[3] In particular, the ICL model restricts banks' ability to recognize credit losses in a timely manner. Delayed recognition of credit losses can reduce bank transparency, making them vulnerable to liquidity risk and to individual and systematic downside tail risk (Bushman and Williams, 2012, 2015).

In the aftermath of the financial crisis, the leaders of the G20 called on both the Financial Accounting Standards Board and the International Accounting Standards Board to explore alternatives to the ICL model. In 2009, the boards established the Financial Crisis Advisory Group, which determined that delays in loan loss recognition under the ICL model led to the understatement of credit losses and overstatement of assets and thus recommended an alternative model that incorporates more forward-looking information. In response to these recommendations, the International Accounting Standards Board issued International Financial Reporting Standard (IFRS) 9, which introduced the expected credit loss (ECL) model.[4,5] In June 2016, the Financial Accounting Standards Board issued Accounting Standards Update

[3] Specifically, delays in the recognition of credit losses resulted in greater increases to loan loss provisions and greater decreases in profitability and regulatory capital during the financial crisis, which led to banks' increased difficulty in replenishing capital and thus further reduced lending (Beatty and Liao, 2011, 2014; Berger and Bouwman, 2013; Acharya and Ryan, 2016).
[4] See IFRS 9 (Financial Instruments), available at https://www.ifrs.org/content/dam/ifrs/project/fi-impairment/ifrs-standard/published-documents/project-summary-july-2014.pdf.
[5] Prior to ECL, International Accounting Standards 39 required banks to recognize and record only incurred loan losses. The ICL model under US Generally Accepted Accounting Principles and International Accounting Standards 39 are regarded as essentially identical (Financial Stability Forum 2009).

2016-13, which introduced the CECL model.[6] Both models replace the ICL model in their respective regions and require banks to incorporate forward-looking information into their expected credit loss provisioning.

In Appendix A, we provide a summary of the differences between these impairment models. Compared to the ICL model, under which banks must identify a trigger event to recognize loan losses, the CECL and ECL models require banks to recognize credit losses in each period since a financial asset's initial origination. Moreover, whereas the ICL model requires banks to rely on historical data and current information in credit loss estimation, the CECL and ECL models require banks to incorporate forward-looking information as well. Though both the ECL and CECL models aim to increase loan loss recognition timeliness by incorporating forward-looking information into the estimation of expected loan losses, they have important differences in the estimations of credit losses. The CECL model requires banks to estimate the credit losses over the lifetime of a financial asset, while the ECL model requires banks to estimate the credit losses differently for assets in different stages. For the CECL model, adoption was voluntary and occurred during a pandemic. U.S. bank regulators also provided CECL transition provision to alleviate the adverse effects of CECL model adoption on regulatory capital. In contrast, ECL model adoption was mandatory and occurred during normal times with no transition provision. Specifically, most IFRS-adopting countries adopted the IFRS 9 and thus, the ECL model, for annual periods beginning on or after January 1, 2018. Abad and Suarez (2018) and Buesa et al. (2020) evaluate the effect of each model on cyclical behavior and demonstrate that the CECL model is less procyclical than the ECL model, though at the cost of a larger increase in loan loss provisions.

[6] See Accounting Standards Update 2016-13 on Financial Instruments—Credit Losses (Topic 326), available at https://www.fasb.org/jsp/FASB/Document_C/DocumentPage?cid=1176168232528&acceptedDisclaimer=true.

In Appendix B, we also summarize the adoption procedure for the CECL model, including disruptions caused by the COVID-19 pandemic. Public banks that are SEC filers (excluding banks eligible to be Smaller Reporting Companies) are required to adopt the CECL model since the fiscal years beginning after December 15, 2019. Other banks are required to adopt this model since fiscal years beginning after December 15, 2022.[7] However, COVID-19 disrupted the mandatory adoption of the CECL model. The enormous uncertainty related to the COVID-19 pandemic and its public health and economic impacts brought unprecedented challenges for banks adopting the CECL model (Bartik et al., 2020). In March 2020, President Donald Trump signed the Coronavirus Aid, Relief, and Economic Security (CARES) Act. The act allowed banks to delay CECL adoption until the first day of the bank's fiscal year that begins after the date when the national emergency concerning the COVID-19 outbreak has ended.[8] In December 2020, President Trump signed the Consolidated Appropriations Act into law, extending the statutory relief until the first day of the fiscal year that begins after the national emergency is terminated, or until January 1, 2022, whichever comes first.[9] In sum, no bank had to adopt the CECL model during the statutory relief period and banks that did so before January 1, 2022, were voluntary adopters.

Accounting Standards Update 2016-13 requires banks to make an adjustment to the opening loan loss allowance and opening retained earnings upon adopting the CECL model. The purpose of the adjustment is to reflect differences in credit loss reserves (accumulated in prior periods) between the ICL and CECL models. Given the potential effect of initial CECL adoption on regulatory capital, in February 2019, regulators issued the Regulatory Capital Rule,

[7] See Accounting Standards Update 2019-10 on Financial Instruments—Credit Losses (Topic 326), available at https://fasb.org/jsp/FASB/Document_C/DocumentPage?cid=1176173775344&acceptedDisclaimer=true.

[8] See Section 4014 of the CARES Act, available at https://www.congress.gov/116/bills/hr748/BILLS-116hr748enr.pdf, and the CARES Act Section 4014 Technical Corrections Act, available at https://www.congress.gov/116/bills/hr6551/BILLS-116hr6551ih.pdf.

[9] See Section 540 of the Consolidated Appropriations Act, available at https://www.congress.gov/116/plaws/publ260/PLAW-116publ260.pdf.

providing a three-year transition provision for adopters with reductions in retained earnings after switching to CECL.[10] This provision allows banks to phase in CECL's day-one adverse effect on regulatory capital over three years. However, in view of the operational challenges caused by the pandemic, on March 31, 2020, regulators issued the Joint Statement on the Interaction of Regulatory Capital Rule, granting an alternative five-year CECL transition provision for CECL-adopting banks.[11] The rule allows banks to delay the CECL's impact on regulatory capital for up to two years. In this way, the cumulative impact on regulatory capital at the end of the transition period's second year can be phased in over the subsequent three years.[12] During our sample period from the first quarter of 2020 through the first quarter of 2021, we find that most CECL-adopting banks choose the five-year CECL transition provision, as opposed to the three-year one.

2.2. Hypothesis development

Our baseline hypothesis focuses on a key objective of the CECL model: whether the new model improves banks' loan loss recognition timeliness.

First, the model removes the "trigger event" requirement. Under ICL, a bank can only recognize a loan loss when a trigger event shows that the borrower is likely to default, which means that the bank would not recognize any loan losses on that loan between the date of the loan's initial origination and the date the probable loss occurs. In contrast, the CECL model

[10] See the Regulatory Capital Rule: Implementation and Transition of the Current Expected Credit Losses Methodology for Allowances and Related Adjustments to the Regulatory Capital Rule and Conforming Amendments to Other Regulations, available at https://www.federalregister.gov/documents/2019/02/14/2018-28281/regulatory-capital-rule-implementation-and-transition-of-the-current-expected-credit-losses.

[11] See the Joint Statement on the Interaction of Regulatory Capital Rule: Revised Transition of the CECL Methodology for Allowances with Section 4014 of the Coronavirus Aid, Relief, and Economic Security Act, available at https://www.federalreserve.gov/supervisionreg/srletters/SR2009a1.pdf.

[12] For example, for banks that adopted CECL on January 1, 2020, and elected the three-year CECL transition provision, the one-time increase of loan loss allowance upon adoption would be phased into regulatory capital over three years (2020–2022). For banks that adopted CECL on January 1, 2020, and elected the five-year CECL transition provision, the increased allowances of the CECL model would not affect regulatory capital during the first two years (2020–2021). The cumulative difference of loan loss allowance at the end of 2021, including the one-time increase of loan loss allowance upon adoption and the accumulated incremental loan loss allowance during 2020–2021, would be phased into regulatory capital over the subsequent three years (2022–2024).

requires banks to estimate the current expected losses in each period after loan originated, enabling more timely recognition of future losses. In an examination of the similar ECL model, López-Espinosa et al. (2021) find that ECL provisions are better than ICL provisions at predicting future bank risk.

Second, the CECL model also requires banks to incorporate more forward-looking information into their loan loss provision estimations, meaning that banks cannot rely solely on historical data and must account for borrowers' current conditions and future macroeconomic conditions.[13] Beatty and Liao (2021) document that analysts incorporate forward-looking information into their forecasted provisions and analysts' forecasts incrementally predict the future nonperforming loans and market returns, suggesting that incorporating more future loss information can improve provision timeliness. Abad and Suarez (2018) and Buesa et al. (2020) model the effect of credit impairment under different standards, and both conclude that forward-looking impairment models enable banks to build up provisions earlier in the cycle.

Consider a bank that uses the probability-of-default method to estimate loan losses. Its loan loss allowance is calculated by multiplying the total loan outstanding by the probability of default by the loss given default. Under the ICL model, managers would estimate the probability of default as zero before a trigger event indicates probable losses (e.g., loan impairment). Thus, the loan loss allowance and provisions will be zero before the trigger event, at which point the provisions would be adjusted too late to reflect the credit risk. Under the CECL model, banks would evaluate the probability of default and loss given default from the date of loan origination and over the lifetime of the contract; they also would incorporate borrowers' historical credit ratings, current conditions, and forecasted macroeconomic

[13] For example, Live Oak Bancshares Inc., used forecasted levels of unemployment as the key macroeconomic variable in forecasting future expected losses under the CECL model.

conditions into the estimation. Compared to the ICL provisions, the CECL provisions can better capture the future impairment information earlier in the loan contract.

We hypothesize that the CECL model will improve loan loss recognition timeliness by removing the trigger event requirement and instead requiring the timely incorporation of forward-looking information into the estimation of expected loan losses.

Our hypothesis is not without tension, however. First, loan loss recognition timeliness may not improve if banks cannot implement the CECL model effectively. This implementation is significantly more complicated than that of other accounting standards because it requires interdependencies across modelling, data management, credit analysis, infrastructure management, and governance (Deloitte, 2018a, 2018b; Gnanarajah, 2018). In addition to developing appropriate models, defining the model's critical parameters, and collecting the necessary data, banks need to build sustainable technology platforms to support the CECL processes and increase governance and oversight efforts to monitor implementation (Deloitte, 2018a, 2018b). Software and hardware upgrades, data retention and processing services, and CECL implementation training are all costly (Gnanarajah, 2018). In addition, the unprecedented nature of the pandemic likely makes it difficult for banks to estimate the effect of future macroeconomic conditions on credit losses.

Second, allowing for discretion in recognizing credit losses has advantages and disadvantages (Bushman and Williams, 2012; Huizinga and Laeven, 2012; Beatty and Liao, 2014). The subjective judgments in the CECL model (such as choosing appropriate models and determining the key parameters in the model) provide more discretion room for banks in recognizing loan losses compared to ICL model. This discretion can allow a bank to avoid recording or recording fewer loan loss provisions, compared to what is done in the pre-CECL adoption. Moreover, the COVID-19 pandemic leads to unique considerations with regard to their CECL implementation. The challenging conditions created by COVID-19 might incentivize managers to rely on the CECL model's latitude to actually delay the recognition of loan loss provisions. Bischof et al. (2021) documents that banks were reluctant to communicate their loan losses during the 2007–2009 financial crisis. Specifically, banks' disclosure of relevant risk exposures came late, and recognition of loan losses was slow. Furthermore, in a pandemic, regulators might practice excessive forbearance to avoid disruptions to the banking system and real economy, such as those caused by bankruptcies (Kroszner and Strahan, 1996; Caballero et al., 2008; Skinner, 2008; Brown and Dinc, 2011). Huizinga and Laeven (2012) find that during the U.S. mortgage crisis, banks overstated the value of distressed assets and their regulatory capital, thus inferring that crisis-era bank balance sheets offer a distorted view of bank financial health due to regulatory forbearance and noncompliance with accounting rules. Therefore, there might be no improvement or even deterioration in loan loss recognition timeliness if, under the CECL model, banks opportunistically delay loan loss recognition.

3. Research design

3.1. Sample selection

From the Compustat Bank database, we obtain a set of public banks from the fourth quarter of 2018 through the first quarter of 2021. Our sample period covers the five quarters before and after January 1, 2020, which is the earliest date when the banks in our sample adopt the CECL model.[14] We manually collect the data on when banks switch to the CECL model by reading their 10-K or 10-Q filings, which we obtain from EDGAR. Specifically, we collect data on whether banks adopted the CECL model and for the adopting banks, the quarter the CECL model was first adopted, and their use of CECL transition provision. We drop banks that do not have a Central Index Key and banks for which the 10-K or 10-Q filings are

[14] In conducting the empirical analyses, we could obtain the Compustat Bank data only up to the second quarter of 2021. Because we need the data on banks' nonperforming loans in the next quarter, our sample ends in the first quarter of 2021.

unavailable in EDGAR because we cannot collect their CECL adoption data.[15] We drop bank-quarter observations with missing values for the baseline regression key variables. Our final sample includes 3,716 bank-quarter observations and 392 unique banks.

Figure 1 shows the status of a bank's CECL adoption and whether the bank elects to use the CECL transition provision. Of 392 banks, 181 adopt the CECL model by the end of our sample period. Of CECL-adopting banks, 110 use the CECL transition provision.

We collect banks' financial data from the Compustat Bank database. We collect stock price data from the Center for Research in Security Prices, GDP data from the Federal Reserve Bank of St. Louis website, and bank-level COVID-19 exposure data from Hassan et al. (2021). From FR Y-9C reports compiled by the Federal Reserve Bank of Chicago, we collect banks' day-one adjustment to their loan loss allowance when adopting the CECL model and banks' loans that are individually evaluated for impairment.[16]

3.2. Regression specification

We estimate the following difference-in-differences regression model to test our main hypothesis pertaining to the effect of the CECL model on banks' loan loss recognition timeliness:[17]

$$LLP_{i,t} = \alpha + \beta_1 CECL_{i,t} \times \Delta NPL_{i,t+1} + \beta_2 CECL_{i,t} + \beta_3 \Delta NPL_{i,t+1} + \beta_4 \Delta NPL_{i,t} + \beta_5 \Delta NPL_{i,t-1} + \beta_6 \Delta NPL_{i,t-2} + \beta_7 NPL_{i,t-3} + \beta_8 SIZE_{i,t} + \beta_9 CAPITAL_{i,t} + \beta_{10} EBP_{i,t} + \beta_{11} \Delta LOAN_{i,t} + Bank\ FE + Quarter\ FE + \varepsilon. \quad (1)$$

The dependent variable is loan loss provisions ($LLP_{i,t}$), calculated as the loan loss provision in quarter t, scaled by the lagged total loans and multiplied by 100. $\Delta NPL_{i,t+1}$ is the change in nonperforming loans from quarter t to quarter t + 1, scaled by the total loans in quarter t. The

[15] The Central Index Key is used to identify corporations that file disclosures with the SEC. If a bank has a missing key, we cannot find its filings in EDGAR.
[16] The data are publicly available at https://www.chicagofed.org/banking/financial-institution-reports/bhc-data.
[17] Balakrishnan et al. (2021) use a similar regression model to examine the effect of a mandate that requires bank auditors to report loan loss recognition timeliness to bank regulators. In their research setting, different countries start adapting to the mandate in different years.

effect of future nonperforming loans on current loan loss provisions is expected to be positive because banks have to account for future expected loan losses in their current loan loss provisions. A larger positive effect indicates timelier loan loss recognition (Beatty and Liao, 2011, 2014; Balakrishnan and Ertan, 2021). Banks that adopt CECL during our sample period are voluntary adopters that adopt in different fiscal quarters within the sample period. $CECL_{i,t}$ is an indicator variable equal to one for the quarter when banks adopt the CECL model and all quarters after it, and zero otherwise.[18] The independent variable of interest is the interaction term between the adoption of the CECL model and the change in future nonperforming loans ($CECL_{i,t} \times \Delta NPL_{i,t+1}$). The coefficient on this variable, β_1, captures the change in loan loss recognition timeliness after banks adopt the CECL model, relative to a group of banks that do not adopt during the sample period. A significantly positive coefficient on $CECL_{i,t} \times \Delta NPL_{i,t+1}$ (i.e., β_1) would support our hypothesis that the switch from the ICL to the CECL model improves banks' loan loss recognition timeliness.

Following prior literature (Hribar et al., 2017; Dou et al., 2018; Balakrishnan and Ertan, 2021), we include a series of control variables that affect loan loss provisions. First, we control for banks' current loan performance by including current changes in nonperforming loans ($\Delta NPL_{i,t}$). Because banks also consider historical loan information when estimating the expected credit losses, we further control for banks' change in nonperforming loans in quarters $t-1$ and $t-2$ ($\Delta NPL_{i,t-1}$ and $\Delta NPL_{i,t-2}$), as well as the level of nonperforming loans in quarter $t-3$ ($NPL_{i,t-3}$). Second, we control for bank-level characteristics that affect banks' regulatory requirements and earnings management incentives. We include as control variables bank size ($SIZE_{i,t-1}$), capital ratio ($CAPITAL_{i,t}$), earnings before loan loss provisions ($EBP_{i,t}$), and change in total loans ($\Delta LOAN_{i,t}$). We include bank fixed effects and year-quarter fixed effects to

[18] Due to the inclusion of bank and quarter fixed effects, $CECL_{i,t}$ effectively captures the traditional difference-in-differences estimator. The main effects of the interaction between the post-adoption dummy variable (which captures the time-series difference) and the treatment bank dummy variable (which captures cross-sectional differences) are absorbed by the fixed effects.

respectively control for time-invariant bank-specific features and economic factors that commonly affect all firms in each quarter. We winsorize all continuous variables at the bottom and top one percent levels. See Appendix C for a summary of variable definitions.

3.3. Descriptive statistics

Table 1 presents the sample distribution by quarter. As shown, 137 banks adopted the CECL model in the first quarter of 2020, none in the second quarter of 2020, 4 in the third quarter of 2020, 18 in the fourth quarter of 2020, and 22 in the first quarter of 2021.[19] By the end of our sample period, nearly half of banks have adopted the CECL model.

Table 2 presents the descriptive statistics for the key variables. The mean of $LLP_{i,t}$ is 0.0837, showing that loan loss provisions are 0.08 percent, on average, of lagged total loans. $CECL_{i,t}$ has a mean of 0.2024, suggesting that the CECL model is in effect for 20.24 percent of bank-quarter observations in our sample. The mean of $\Delta NPL_{i,t+1}$ is 0.0095, showing that the increase in one-quarter-ahead nonperforming loans is around 0.01 percent, on average, of current total loans.

4. Empirical results

4.1. Effect of CECL model adoption on loan loss recognition timeliness

Table 3 reports the results of the test of whether loan loss recognition timeliness improves after switching from the ICL model to the CECL model. Column 1 reports the results of the regressions estimated using the difference-in-differences model, as indicated in Equation (1). The coefficient on $CECL_{i,t} \times \Delta NPL_{i,t+1}$ is 0.1421, which is statistically significant at the 1 percent level (t-value of 5.95), showing that loan loss recognition timeliness improves after banks switch from ICL to CECL.

[19] During our sample period, 181 banks adopt the CECL model. Table 1 shows 178 adopters by the first quarter of 2021 because three banks have missing values for the baseline regression's variables.

The signs of the estimated coefficients on the bank-level control variables are generally consistent with prior findings. The coefficients on $\Delta NPL_{i,t}$, $\Delta NPL_{i,t-1}$, and $NPL_{i,t-3}$ are positive and statistically significant, suggesting that banks incorporate historical and current loan performance into their loan loss provisions. The coefficient on $\Delta LOAN_{i,t}$ is significantly positive, showing that banks that experience an increase in total loans in the current period record more loan loss provisions. The coefficient on $EBP_{i,t}$ is significantly positive, consistent with banks smoothing earnings through provisioning practice, that is, recognizing more loan losses when current period earnings are high and vice versa (Liu and Ryan, 2006; Bushman and Williams, 2012; Kilic et al., 2013).

The identifying assumption in our difference-in-differences regressions is that both CECL model adopters and nonadopters have parallel trends in loan loss recognition timeliness prior to CECL adoption. A violation of the parallel trend assumption may suggest that economic conditions or other accounting considerations were already causing CECL model adopters to have timelier loan loss recognition even prior to the adoption. We therefore run a parallel trend test to investigate pre-adoption trends for CECL adopters and nonadopters. Column 2 reports the results of this test, in which we replace $CECL_{i,t}$ with three indicator variables: $CECL\_PRE1_{i,t}$, $CECL\_POST1_{i,t}$, and $CECL\_POST2+_{i,t}$. The coefficient on $CECL\_PRE1_{i,t} \times \Delta NPL_{i,t+1}$ is insignificant, suggesting that there is no significant difference in loan loss recognition timeliness in the pre-adoption period between CECL adopters and nonadopters. The coefficients on $CECL\_POST1_{i,t} \times \Delta NPL_{i,t+1}$ and $CECL\_POST2+_{i,t} \times \Delta NPL_{i,t+1}$ are positive and statistically significant, showing that loan loss recognition timeliness improves after banks switch from the ICL to the CECL model. Column 2 of Table 3 shows that CECL adopters and nonadopters have similar trends in loan loss recognition timeliness prior to adoption, which supports the parallel trend assumption associated with the difference-in-differences estimation.

We now perform a series of robustness tests to confirm our inference that the CECL model enhances banks' loan loss recognition timeliness. In Table 4, Panel A, we re-estimate our results using indicators of expected loan losses other than $\Delta NPL_{i,t+1}$. Column 1 reports the results of the regressions estimated using the change in nonperforming loans in quarters $t + 1$ ($\Delta NPL_{i,t+1}$) and $t + 2$ ($\Delta NPL_{i,t+2}$) as indicators of banks' current estimation of future loan losses, as opposed to Equation (1), which uses only $\Delta NPL_{i,t+1}$. The coefficients on $CECL_{i,t} \times \Delta NPL_{i,t+1}$ and $CECL_{i,t} \times \Delta NPL_{i,t+2}$ are 0.1362 and 0.1854, respectively, both of which are statistically significant. These outcomes further corroborate that the CECL model improves banks' loan loss recognition timeliness.

Next, we run analyses that replace $\Delta NPL_{i,t+1}$ in Equation (1) with macroeconomic indicators that affect banks' expectations of future loan losses because, under the CECL model, macroeconomic indicators should be considered in accounting for future credit losses.[20] We examine whether banks record loan loss provisions that account for those current macroeconomic conditions that might suggest future deterioration in the loan portfolios. Note that our regression also controls for variables that signify past and current deterioration in the loan portfolios (e.g., $\Delta NPL_{i,t-1}$ and $\Delta NPL_{i,t}$). Hence, we assume that contemporaneous macroeconomic indicators are predictors of future loan losses.[21]

First, we replace $\Delta NPL_{i,t+1}$ with GDP growth in the current quarter ($GDPGROWTH_{i,t}$). A higher GDP growth rate is expected to reduce future loan losses because borrowers will be more likely to repay their loans when the economy is stronger. Column 2 reports the results of the regression with $GDPGROWTH_{i,t}$. The coefficient on $CECL_{i,t} \times GDPGROWTH_{i,t}$ is –0.3226, which is statistically significant at the 1 percent level (t-value of –16.23). By showing that CECL adopters are more likely to incorporate future macroeconomic conditions into their loan

[20] In this paper, both changes in nonperforming loans and macroeconomic factors are indicators of future credit losses.

[21] The results with one-quarter-ahead macroeconomic indicators are qualitatively the same.

loss provisions, we also provide evidence that adopting banks are more timely than nonadopters in their recording of expected loan losses.

Second, adoption of the CECL model overlaps with the COVID-19 pandemic. The pandemic clearly had an important effect on banks, and many banks discuss its impact on their loan losses during conference calls and in regulatory filings and press releases. Thus, any banks adopting it in 2020 and early 2021 would consider the pandemic's potential impact on their loan portfolios.[22] To measure a bank's exposure to the pandemic's adverse impact, we use the frequency of COVID-19 mentions in conference calls, scaled by call length (Hassan et al., 2021). Column 3 reports the results of the regression with the change in bank-level COVID-19 exposure ($\Delta COVID19_{i,t}$). Considering that banks first become exposed to the COVID-19 pandemic starting in the first quarter of 2020, we restrict our sample to the first quarter of 2020 to the first quarter of 2021. We find that the coefficient on $CECL_{i,t} \times \Delta COVID19_{i,t}$ is positive and statistically significant, suggesting that CECL-adopting banks record timelier loan losses. Collectively, the findings in Table 4, Panel A indicate that our inference that CECL model adoption enhances banks' loan loss recognition timeliness is robust to using indicators of banks' expected loan losses other than $\Delta NPL_{i,t+1}$.

Next, we consider the robustness of our inference to alternative samples. In our sample, most banks adopt the CECL model in the first quarter of 2020, possibly because they were simply following their original plan, even though the CARES Act gave them the option of delaying. Banks that adopt CECL in subsequent quarters have more time to prepare for the model's implementation and can better estimate the pandemic's effect on loan losses under the CECL regime. We examine whether the CECL model's effect on loan loss recognition

[22] Truist Financial Corporation's 10-Q report for the first quarter of 2020 discusses changes in the factors influencing its estimations of loan loss allowance: "The commercial allowance for loan and lease losses (ALLL) increased $411 million primarily driven by a more pessimistic outlook with respect to future economic conditions driven by the COVID-19 pandemic and specific consideration of the risks associated with exposures to certain industries, including oil and gas, hospitality, and airlines, as well as lending to small businesses."

timeliness varies depending on when banks adopt it. Table 4, Panel B shows the results. In Column 1, we keep banks that adopt CECL in the first quarter of 2020 and those that do not adopt it during our sample period. The coefficient on $CECL_{i,t} \times \Delta NPL_{i,t+1}$ is positive and statistically significant, showing that loan loss recognition timeliness improves after banks adopt the CECL model in the first quarter of 2020. In Column 2, we retain banks that adopt the CECL model after the first quarter of 2020 and banks that do not adopt it during our sample period. The coefficient on $CECL_{i,t} \times \Delta NPL_{i,t+1}$ is again positive and statistically significant. The results show that the effect of the switch to CECL on loan loss recognition timeliness is present both for banks that adopt the CECL model in the first quarter of 2020 and those that adopt in later quarters.

Next, we consider whether our findings are sensitive to omitted variable bias despite the large number of control variables included in Equation 1. We address this issue by using the test developed by Oster (2019), which is widely used in recent research (e.g., Call et al., 2018; Heimer et al., 2019; Argyle et al., 2021; Bernard et al., 2021; Dixon et al., 2021). The test estimates the model both with and without control variables and then evaluates the differences in the coefficients on the treatment variables and the explanatory power between the two models. Oster (2019) proposes a coefficient of proportionality (δ), which is calculated based on the pre-defined maximum R-square and the movements of both the coefficient of interest and the R-square of the regression models with and without controls. δ can be used to test the sensitivity of our results to omitted variables bias. A δ of 1.00 means that to result in a treatment effect of zero, the unobservable controls would need to be as important as the observable controls. The more δ exceeds 1.00, the less likely it is that the omitted variables can explain the treatment effect.

Table 4, Panel C reports the results. Column 1 shows the results estimated from the model without control variables, in which we keep only $CECL_{i,t} \times \Delta NPL_{i,t+1}$, $CECL_{i,t}$, and

$\Delta NPL_{i,t+1}$. Column 2 shows the results estimated from the model with controls, as indicated by Equation (1). Following Oster (2019), we set the maximum R–squared to be 1.3 times the R–square for the regression model with control variables. δ is 4.472, suggesting that to overturn our results, the unobservable controls would need to be 4.472 times as important as the observable controls. These results mitigate concerns that the observed differences in loan loss recognition timeliness between CECL model adopters and nonadopters are driven by omitted variables instead of CECL adoption.

Finally, we perform a placebo test to investigate whether events that occur simultaneously with CECL model adoption could be driving our documented changes in loan loss recognition timeliness. We artificially generate 1,000 sets of pseudo adopters randomly selected from all banks. The distribution of each set of pseudo adopters is the same as that of actual CECL model adopters. $PSEUDO\_CECL_{i,t}$ is an indicator variable that equals one for the quarter when the pseudo adopters adopt the CECL model and all quarters after it, and zero otherwise. We then estimate Equation (1) for each pseudo adopter set. We expect that loan loss recognition timeliness will not improve for these artificial adopters because they do not in fact adopt the CECL model.

Figure 2 shows the empirical distribution of the coefficient on $PSEUDO\_CECL_{i,t} \times \Delta NPL_{i,t+1}$ across 1,000 estimations. The results indicate that the effect of the switch to the CECL model on loan loss recognition timeliness that we document in our main test is unlikely to be spurious: the magnitude of the maximum coefficient on $PSEUDO\_CECL_{i,t} \times \Delta NPL_{i,t+1}$ estimated in the placebo test (0.0886) is much smaller than the magnitude of the coefficient on $CECL_{i,t} \times \Delta NPL_{i,t+1}$ from Column 1 in Table 3 (0.1421). The average of the coefficients on $PSEUDO\_CECL_{i,t} \times \Delta NPL_{i,t+1}$ (0.0048) also is substantially smaller than our point estimation on $CECL_{i,t} \times \Delta NPL_{i,t+1}$ from Column 1 in Table 3 (0.1421). In comparison, the average of the coefficients on the other control variables across the 1,000 pseudo samples is similar to the coefficients on these control variables from Column 1 in Table 3.[23] The results show that banks' loan loss recognition timeliness is not sensitive to pseudo adoption of the CECL model, which is both consistent with our expectations and further addresses the omitted variable issue.

4.2. Cross-sectional variation in the effect of CECL model adoption on loan loss recognition timeliness

Thus far, we argue and present evidence that switching from the ICL to the CECL model can improve banks' loan loss recognition timeliness. In this section, we perform cross-sectional analyses to explore whether the positive effect of the CECL model varies cross-sectionally with banks' risk-taking and whether banks opt for CECL transition provision. These analyses enable us to better understand variations in the effect of CECL model adoption and the channels through which it affects loan loss recognition timeliness.

4.2.1. Cross-sectional variation with ICL constraints

First, we explore whether improvement in loan loss recognition timeliness under the CECL model varies with an important constraint (i.e., the trigger event requirement) that inhibits timely loan loss recognition under the ICL model. Under the ICL model, a bank can recognize loan losses only when a trigger event shows that the borrower is likely to default. If eliminating this requirement via CECL model adoption indeed improves loan loss recognition timeliness, we would expect improvements to be more pronounced for banks that are more constrained under the ICL model (i.e., more likely to delay loan loss recognition due to the trigger event requirement).

We argue that riskier banks are more constrained by the trigger event requirement. In terms of lending, riskier banks tend to fund riskier loans and are expected to have more non-

[23] For example, the average of the coefficients on $SIZE_{i,t}$ across the 1,000 pseudo samples is 0.0334, which is similar to the point estimation on $SIZE_{i,t}$ in Column 1 in Table 3 (i.e., 0.0347).

performing and defaulting loans (Laeven and Levine, 2009; Houston et al., 2010; Acharya and Naqvi, 2012). The delay in loan loss recognition caused by the trigger event requirement thus should be more significant for riskier banks, which should have more expected loan losses over the lifetime of their loans. Without the trigger event requirement, riskier banks can (and in fact must) record loan loss provisions based on expected loan losses at the end of each fiscal period. In other words, compared to less risky banks, riskier banks should show a larger improvement in loan loss recognition timeliness after switching from the ICL to CECL model.

Column 1 of Table 5 reports the results for the cross-sectional variations in risk-taking. We follow the methodology used in Christensen et al. (2016) and Jayaraman and Wu (2019) to conduct the test. Specifically, we categorize CECL-adopting banks as high (low) risk-taking if their pre-adoption risk-taking is greater (smaller) than the median value for CECL-adopting banks. We measure risk-taking as the Z-score in the pre-adoption period. Following Laeven and Levine (2009) and Houston et al. (2010), we calculate the Z-score as minus one (–1) times the natural logarithm of the sum of the average ROA and the average capital ratio divided by the standard deviation of ROA. $CECL\_HRISK_{i,t}$ ($CECL\_LRISK_{i,t}$) is an indicator variable that equals one for the quarter when high (low) risk-taking banks adopt the CECL model and all quarters after it, and zero otherwise. We replace $CECL_{i,t}$ in Equation (1) with the above two indicator variables and focus on the difference in the coefficients on $CECL\_HRISK_{i,t} \times \Delta NPL_{i,t+1}$ and $CECL\_LRISK_{i,t} \times \Delta NPL_{i,t+1}$. The coefficients on $CECL\_HRISK_{i,t} \times \Delta NPL_{i,t+1}$ and $CECL\_LRISK_{i,t} \times \Delta NPL_{i,t+1}$ are 0.2126 and 0.0741, respectively, both of which are statistically significant. These outcomes suggest that the positive effect of the switch to the CECL model on loan loss recognition timeliness exists for both high and low risk-taking banks. We find that the coefficient on $CECL\_HRISK_{i,t} \times \Delta NPL_{i,t+1}$ is significantly larger than that on $CECL\_LRISK_{i,t} \times \Delta NPL_{i,t+1}$, showing that the improvement effect of the CECL model on loan loss recognition timeliness is more pronounced for banks that take more risk in the pre-adoption period.

Moreover, we argue that banks that have more heterogeneous loans are more constrained by the ICL model. Under ICL, banks determine loan loss allowance and provisions differently for homogenous loans and heterogeneous loans (Liu and Ryan, 1995, 2006; Bhat et al., 2021). For homogeneous loans, banks estimate their losses at the portfolio level based on historical statistical information. For example, banks might calculate loan loss allowance for these loans based on their historical loan default rate and rely less on subjective judgments on these loans. For heterogeneous loans, banks estimate their losses at the individual-loan level based on loan officers' judgments on each loan. In making such judgments, banks rely on the occurrence of trigger events related to each individual loan; thus, loss recognition for heterogeneous loans is more constrained by the trigger event requirement than that for homogeneous loans. Prior studies support that loan loss recognition is less timely among banks with a high proportion of heterogeneous loans (Liu and Ryan, 1995, 2006). If removing the trigger event requirement via the CECL modelimproves loan loss recognition timeliness, then this improvement should be more pronounced among banks with higher proportions of heterogenous loans that are individually evaluated for impairment.

In Column 2, we define $CECL\_HINDLOAN_{i,t}$ and $CECL\_LINDLOAN_{i,t}$ based on banks' proportion of individually evaluated loans in the pre-adoption period (Beatty and Liao, 2021). $CECL\_HINDLOAN_{i,t}$ ($CECL\_LINDLOAN_{i,t}$) is an indicator variable that equals one during and after the quarter when CECL-adopting banks adopt the CECL model having a high (low) pre-adoption proportion of loans individually evaluated for impairment. We find that the coefficients on $CECL\_HINDLOAN_{i,t} \times \Delta NPL_{i,t+1}$ and $CECL\_LINDLOAN_{i,t} \times \Delta NPL_{i,t+1}$ are positive and statistically significant and that the coefficient on $CECL\_HINDLOAN_{i,t} \times \Delta NPL_{i,t+1}$ is significantly larger than that on $CECL\_LINDLOAN_{i,t} \times \Delta NPL_{i,t+1}$. The results show that the effect of the CECL model is more pronounced among banks with higher proportions of loans that are individually evaluated for impairment.

Taken together, the results in Table 5 show that the positive effect of the switch to the CECL model on banks' loan loss recognition timeliness is stronger for riskier banks or banks with more heterogeneous loans. The finding is consistent with banks that are more restricted in recognizing loan losses due to the trigger event requirement having more timely loan loss recognition after switching to the CECL model. The findings thus support removal of the trigger event requirement as a channel through which the CECL model improves banks' loan loss recognition timeliness.

4.2.2. Cross-sectional variation with the election of CECL transition provision

Second, we explore whether the improvement in loan loss recognition timeliness due to the CECL model's introduction varies with the CECL transition provision. An important component of banks' provisioning practice is its potential impact on regulatory capital. Regulators view capital adequacy as a key element of bank safety and soundness (Burhouse et al., 2003; Beatty and Liao, 2014). Capital inadequacy leads to increased costs of raising new capital (Van den Heuvel, 2009) and a decreased probability of survival and market share (Berger and Bouwman, 2013). In particular, banks with low capital have incentives to cut lending to avoid capital inadequacy (Bernanke et al., 1991; Beatty and Liao, 2011). Banks that adopt the CECL model during the COVID-19 pandemic need to incorporate the economic downturn's adverse impact into their loan loss estimation, which substantially increases loan loss provisions. Given that loan loss provisions reduce retained earnings, which is a key component of a bank's common equity tier 1 capital, CECL adoption increases banks' concerns about regulatory capital inadequacy. Indeed, prior literature finds that banks use their provisioning discretion to meet regulatory capital requirements (Moyer, 1990; Beatty et al., 1995; Ahmed et al., 1999; Huizinga and Laeven, 2012).

To mitigate banks' concerns about capital inadequacy upon adopting the CECL model, bank regulators introduced a CECL transition provision for CECL-adopting banks. As discussed in Section 2.1, the transition provision takes two alternative forms. The three-year transition provision allows banks to phase in the CECL's impact on regulatory capital over three years. Alternatively, the five-year transition provision allows CECL-adopting banks to delay the day-one adverse effects of CECL on regulatory capital for two years and then phase in the CECL's cumulated impact on regulatory capital over the subsequent three years. Banks that opt for one of the CECL transition provisions can delay or spread the switch's impact on regulatory capital over a longer period, thereby alleviating regulatory pressure in the current period while still achieving more timely loan loss recognition. In other words, banks that opt for the CECL transition provision have the capacity to record more loan losses. Consequently, we predict that the positive effect of the CECL model on loan loss recognition timeliness will be more pronounced for banks that use the CECL transition provision.

We first examine the effect of the switch to the CECL model on regulatory capital and whether use of the CECL transition provision alleviates this effect. We estimate the difference-in-differences model to test the prediction. Table 6, Panel A reports the results. The dependent variable is the tier-one risk-adjusted capital ratio ($CAPR1_{i,t}$). In Column 1, the independent variable of interest is $CECL_{i,t}$. We find that the coefficient on $CECL_{i,t}$ is negative and statistically significant, consistent with the CECL model decreasing banks' regulatory capital. In Column 2, we replace $CECL_{i,t}$ with $CECL\_TRAN_{i,t}$ and $CECL\_NOTRAN_{i,t}$ and focus on the difference between the coefficients on these two indicator variables. $CECL\_TRAN_{i,t}$ ($CECL\_NOTRAN_{i,t}$) is an indicator variable that is equal to one during and after the quarter when the CECL-adopting banks adopt the CECL model with (without) the CECL transition provision, zero otherwise. We find that the coefficient on $CECL\_TRAN_{i,t}$ is insignificant, but the coefficient on $CECL\_NOTRAN_{i,t}$ is negative and statistically significant, showing that the decrease in regulatory capital after switching to the CECL model is concentrated among banks that do not use the transition provisions. This result suggests that CECL transition provisions help banks reduce the adverse effect of the CECL model on regulatory capital.

Panel B, Table 6 reports the results for the cross-sectional variations with the election of CECL transition provision in the CECL model's effect on loan loss recognition timeliness. We replace $CECL_{i,t}$ in Equation (1) with the above two indicator variables and focus on the difference between the coefficients on $CECL\_TRAN_{i,t} \times \Delta NPL_{i,t+1}$ and $CECL\_NOTRAN_{i,t} \times \Delta NPL_{i,t+1}$. The coefficient on $CECL\_TRAN_{i,t} \times \Delta NPL_{i,t+1}$ is 0.1855, which is statistically significant at the 1 percent level (t-value of 6.62), and the coefficient on $CECL\_NOTRAN_{i,t} \times \Delta NPL_{i,t+1}$ is 0.0422, which is insignificant. We further find that the coefficient on $CECL\_TRAN_{i,t} \times \Delta NPL_{i,t+1}$ is significantly larger than that on $CECL\_NOTRAN_{i,t} \times \Delta NPL_{i,t+1}$. The results show that the effect of the CECL model exists only among banks that use the CECL transition provision.

In Column 2, we divide the CECL-adopting banks into four groups based on their use of the CECL transition provision and whether they have a low or high pre-adoption capital ratio. $CECL\_TRAN\_LCAP_{i,t}$ ($CECL\_NOTRAN\_LCAP_{i,t}$) is an indicator variable that equals one during and after the quarter when the CECL-adopting banks adopt the CECL model with (without) the CECL transition provision and having a low pre-adoption capital ratio, and zero otherwise. $CECL\_TRAN\_HCAP_{i,t}$ ($CECL\_NOTRAN\_HCAP_{i,t}$) is an indicator variable that equals one during and after the quarter when the CECL-adopting banks adopt the CECL model with (without) the CECL transition provision and having a high pre-adoption capital ratio, and zero otherwise. We replace $CECL_{i,t}$ in Equation (1) with the above four indicator variables and focus on the difference between the coefficients on $CECL\_TRAN\_LCAP_{i,t} \times \Delta NPL_{i,t+1}$ and $CECL\_NOTRAN\_LCAP_{i,t} \times \Delta NPL_{i,t+1}$ and the difference between the coefficients on $CECL\_TRAN\_HCAP_{i,t} \times \Delta NPL_{i,t+1}$ and $CECL\_NOTRAN\_HCAP_{i,t} \times \Delta NPL_{i,t+1}$.

The coefficient on $CECL\_TRAN\_LCAP_{i,t} \times \Delta NPL_{i,t+1}$ is positive and statistically significant, but the coefficient on $CECL\_NOTRAN\_LCAP_{i,t} \times \Delta NPL_{i,t+1}$ is insignificant. The results show that for low capital banks, the effect of the CECL model is pronounced only for banks that use the CECL transition provision. In contrast, the coefficients on $CECL\_TRAN\_HCAP_{i,t} \times \Delta NPL_{i,t+1}$ and $CECL\_NOTRAN\_HCAP_{i,t} \times \Delta NPL_{i,t+1}$ are both statistically significantly positive, and these two coefficients show no significant differences. The results suggest that for high capital banks, using the CECL transition provision does not change the impact of CECL adoption on loan loss recognition timeliness. The results in Column 2 suggest that the CECL transition provision is most likely to improve loan loss recognition timeliness among banks with low regulatory capital prior to CECL adoption.

These results are consistent with our predictions that the positive effect of the CECL model on loan loss recognition timeliness is stronger for banks that use CECL transition provision, which mitigates their concern about inadequate regulatory capital. The findings suggest that the CECL model can improve banks' loan loss recognition timeliness more when the banks are less concerned about regulatory capital inadequacy.

4.3. Supplementary analyses

4.3.1. Impact of pre-adoption loan loss recognition timeliness on the switch's day-one effect on loan loss allowance

In this section, we test the association between loan loss recognition timeliness during the ICL regime and the cumulative-effect adjustment to the loan loss allowance upon adopting the CECL model. Banks that adopt CECL are required to use a modified-retrospective transition approach to deal with the opening balances of their loan loss reserves, as the reserves must reflect the use of CECL to account for prior-period reserves.

On the one hand, CECL-adopting banks with less timely loan loss recognition during the ICL regime might experience a larger catch-up effect in their loan loss allowance at the start of CECL adoption. This catch-up can occur if banks had accumulated lower loan losses during the ICL regime because of the trigger event requirement. After CECL model adoption, these banks must recognize loan losses earlier, and the COVID-19 pandemic makes it even harder to delay recognition further. On the other hand, the cumulative-effect adjustment to loan loss allowance could be larger for banks that recognize loan losses in a more timely fashion under ICL. Christensen et al. (2016) refer to this phenomenon as the hysteresis effect. For these banks, the prior provisioning practice may reflect institutional, market, and cultural forces that are still in play when CECL is introduced.[24] Thus, if such forces persist, those banks that practice timely loan loss recognition under the ICL model under the ICL model could continue to have timelier loan loss recognition after switching to the CECL model.

To test this effect, we estimate an OLS model based on a sample of banks that adopt CECL during our sample period; we restrict the sample to the adoption quarter. The dependent variable is $\Delta ALW_{i,day\text{-}one}$, calculated as the day-one adjustment to the loan loss allowance when banks adopt the CECL model, divided by the lagged loan loss allowance. The independent variable is the loan loss recognition timeliness in the quarter before banks adopt CECL. We construct three distinct measures of pre-adoption loan loss recognition timeliness: $LLRT1_{i,pre}$, $LLRT2_{i,pre}$, and $LLRT3_{i,pre}$. We also include several control variables that may affect the day-one cumulative adjustment to the loan loss allowance.

Table 7, Column 1 reports the results of the regressions estimated using the stock measure of loan loss recognition timeliness ($LLRT1_{i,pre}$). We calculate the stock measure as the loan loss reserves at quarter *t* divided by the nonperforming loans at quarter *t* (Beatty and Liao, 2011). The estimated coefficient on $LLRT1_{i,pre}$ is –0.0158, which is statistically significant at the 10 percent level (*t*-value = –1.94). This result shows that banks with less timely loan loss

[24] For example, Kanagaretnam et al. (2014) shows that banks' provisioning choice is affected by their inherent culture.

recognition under the ICL regime make a larger adjustment to their loan loss allowance. In Column 2, we use the flow measure of loan loss recognition timeliness ($LLRT2_{i,pre}$), calculated as the difference in the adjusted R^2 from two regression models on loan loss provision (Beatty and Liao, 2011).[25] We find that the coefficient on $LLRT2_{i,pre}$ is negative but statistically insignificant. In Column 3, we use the market-based C-Score as our third measure of loan loss recognition timeliness ($LLRT3_{i,pre}$). We follow Khan and Watts (2009) and estimate the annual cross-sectional model regressing net income on stock returns. Then, we calculate the C-Score as the association between the negative stock market returns and net income.[26] Again, we find that the coefficient on $LLRT3_{i,pre}$ is negative and statistically significant at the 5 percent level (*t*-value = –2.18). Taken together, the results in Table 7 show that banks that are less timely in recording loan losses under the ICL regime make a larger day-one adjustment to their loan loss allowance after switching to the CECL model. The results are consistent with these banks needing to catch up with banks that have timelier loan loss recognition under the ICL regime.

4.3.2. Effect of the CECL model on bank lending

In this section, we test the economic consequences of the switch to the CECL model on bank lending. Ex ante, the switch's effect on bank lending is unclear. Banks that switch to the CECL model may decrease lending compared to banks that do not. The switch to the CECL model results in a sudden increase in loan loss provisions. For existing loans, additional loss provisions are needed. For new loans, loss provisions must be recorded immediately. Such an

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[25] Specifically, the two regression models are as follows: $LLP_t = \alpha_0 + \alpha_1\,\Delta NPL_{t-2} + \alpha_2\,\Delta NPL_{t-1} + \alpha_3\,Capital\ R1_t + \alpha_4\,EBP_t + \varepsilon_t$ and $LLP_t = \alpha_0 + \alpha_1\,\Delta NPL_{t-2} + \alpha_2\,\Delta NPL_{t-1} + \alpha_3\,\Delta NPL_t + \alpha_4\,\Delta NPL_{t+1} + \alpha_5\,Capital\ R1_t + \alpha_6\,EBP_t + \varepsilon_t$. $Capital\ R1_t$ is the tier-one risk-adjusted capital ratio at the beginning of the quarter, divided by 100. A higher flow measure indicates timelier loan loss recognition. The flow measure is the adjusted R^2 from the second model minus that from the first model.

[26] Specifically, the regression model is as follows: $NI_i = \beta_0 + \beta_1 D_i + Returns_i \times (\mu_1 + \mu_2 SIZE_i + \mu_3\,MB_i + \mu_4\,LEV_i) + D_i \times Returns_i \times (\lambda_1 + \lambda_2 SIZE_i + \lambda_3 MB_i + \lambda_4 LEV_i) + (\delta_1 SIZE_i + \delta_2 MB_i + \delta_3 LEV_i + \delta_4 D_i \times SIZE_i + \delta_5 D_i \times MB_i + \delta_6\,D_i \times LEV_i) + \varepsilon_t$. In the model, NI_i is net income divided by the lagged market value of equity. $Returns_i$ is the quarterly returns compounded from the monthly returns beginning the month after the fiscal quarter end. D_i is an indicator variable that equals 1 for negative returns, and zero otherwise. $SIZE_i$ is the logarithm of the market value of equity. MB_i is the ratio of the market value of equity to the book value of equity. LEV_i is the ratio of the book value of long-term debt divided by the market value of equity. We calculate the C-Score as $\lambda_1 + \lambda_2 SIZE_i + \lambda_3 MB_i + \lambda_4 LEV_i$.

increase in loan loss provisions, which is likely to be significant due to the pandemic, can put banks under great earnings and regulatory capital pressure and thus decrease lending. Implementing the CECL model also requires banks to continually assess borrowers' creditworthiness and loan default risk by incorporating banks' predictions of future economic conditions (Deloitte, 2018a, 2018b; Gnanarajah, 2018). The increased risk management costs may also reduce banks' willingness to make new loans. For example, Ertan (2021) documents that banks switching from the ICL to the ECL model reduces lending to small and medium-sized enterprises due to concerns about decreased earnings and the difficulties in implementing the ECL model.

However, banks that switch to the CECL model may increase lending compared to banks that do not. The CECL model improves bank transparency because it enables loan loss provisions to reflect future loan risk earlier in the cycle, and it improves banks' credit risk management (López-Espinosa et al., 2021). This improvement in transparency reduces banks' cost of raising external capital, which in turn enables them to increase lending (Balakrishnan and Ertan, 2019).

We estimate the difference-in-differences model to test the prediction, the results of which are reported in Table 8. The dependent variable is the change in total loans in quarter t ($\Delta LOAN_{i,t}$) or t + 1 ($\Delta LOAN_{i,t+1}$). The independent variable of interest is $CECL_{i,t}$, an indicator variable that equals one for the quarter when banks adopt the CECL model and all quarters after it, and zero otherwise. Following prior literature, we also include a series of bank-level control variables (Beatty and Liao, 2011; Ertan, 2021).

Column 1 reports the results of the regressions estimated using the change in total loans in quarter t ($\Delta LOAN_{i,t}$) as the dependent variable. The coefficient on $CECL_{i,t}$ is –0.0069, which is statistically significant at the 5 percent level (t-value of –2.08). This outcome shows that banks that adopt the CECL model reduce lending relative to nonadopters. Column 2 reports the regression results obtained from using the change in total loans in quarter $t + 1$ ($\Delta LOAN_{i,t+1}$) as the dependent variable. We again find that the coefficient on $CECL_{i,t}$ is negative and statistically significant. Collectively, these results show that CECL-adopting banks are more cautious with lending during the COVID-19 pandemic, possibly due to concerns about capital inadequacy and reduced earnings.

5. Conclusion

In this paper, we examine the effect of the switch to the CECL model on loan loss recognition timeliness. Motivated by the extensive criticism of the ICL model for its inability to reflect future loan losses in a timely manner, the Financial Accounting Standards Board introduced the CECL model to improve the informativeness and timeliness of loan loss recognition. Using data from public U.S. banks from the fourth quarter of 2018 to the first quarter of 2021, we find that the CECL model improves banks' loan loss recognition timeliness. We find that this improvement is more pronounced among riskier banks and banks with higher proportions of heterogeneous loans, suggesting that removal of the trigger event requirement is one channel through which the CECL model facilitates this improvement. We further find that the effect of the CECL model is stronger for banks that use the CECL transition provision, which allows banks to delay or spread the negative effect of CECL adoption on regulatory capital over a greater number of years. This result suggests that the CECL model improves loan loss recognition timeliness more when banks are less concerned about regulatory capital inadequacy and highlights the important role of regulatory actions in facilitating implementation of accounting standards.

Compared to typical adoptions of accounting standards, a unique feature of the CECL model is that its mandatory adoption was delayed by Congress due to the onset of the COVID-19 pandemic. This delay led to a substantial number of banks voluntarily adopting the CECL model in different fiscal quarters, with some opting for the CECL transition provision to mitigate adverse impacts on regulatory capital. In other words, the staggered adoption created significant heterogeneity in the adoption. Hence, the switch to the CECL model offers us the opportunity to study the dynamics in the accounting standards adoption in times of macroeconomic difficulties.

We acknowledge that the nature of the CECL adoption setting also limits our ability to draw strong causal inferences on its effects. First, we cannot rule out entirely the possibility that other concurrent regulatory or economic changes during the COVID-19 pandemic drive our results. What might mitigate this concern are results of the Oster (2019) test and placebo test showing that omitted variables are unlikely to drive the effect on loan loss recognition timeliness that we observe for banks that switch to the CECL model. Second, as CECL adoption is voluntary during our sample period, we may not completely address the endogeneity issues associated with unobservable differences between CECL adopters and non-adopters. We attempt to mitigate this concern using a parallel trend test showing that adopters and non-adopters share similar loan loss recognition trends in the pre-adoption period. Finally, the CECL model's effect on banks' loan loss recognition timeliness is estimated for public banks that voluntarily adopt CECL. Due to this selection, the estimated effect might not be generalizable to other banks, such as banks that will later mandatorily adopt CECL or private banks that might lack oversight from investors and auditors.

Future research might examine whether the effects documented in our paper persist in the long run (e.g., when the pandemic ends or becomes endemic). Relatedly, such research might assess how loan loss recognition timeliness differs between voluntary and mandatory CECL adopters when the CECL model is eventually mandated for all banks. Other outcomes of CECL adoption, including long-term real effects (e.g., procyclicality in bank lending, spillover effects on regulatory enforcement, and impact on borrowers' financing and operations), also would be interesting avenues for future research.

We provide supplementary early evidence of reduced lending in our paper. However, caution is advised when attributing this outcome to CECL adoption. Understandably, studies on real outcomes of accounting are vulnerable to endogeneity concerns because of confounding effects and unique political and economic events, which are especially prevalent during the

COVID-19 pandemic. Hence, more evidence of the effect of CECL adoption after the (hopefully quick) end of the pandemic would be helpful.

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Appendix

Appendix A: Summary of differences between three impairment models

Model	When do banks recognize credit losses?	What information is required in credit loss estimation?	How is estimate conducted?
ICL	Each period after a trigger event shows probable losses occur	Historical data and current information	Only incurred credit losses
CECL	Each period since origination of the financial asset	Historical data and current and forward-looking information.	Lifetime expected credit losses
ECL	Each period since origination of the financial asset	Historical data and current and forward-looking information.	For assets classified as stage 1 (no "significant increase in credit risk"), 12-month expected credit losses For assets classified as stage 2 ("significant increase in credit risk") or stage 3 ("impaired financial assets"), lifetime expected credit losses

Appendix B: Adoption procedure for the current expected credit loss (CECL) model

Mandatory adoption (Original plan)	Public banks that meet the definition of an SEC filer, excluding banks eligible to be smaller reporting companies	Other banks
	Effective for fiscal years beginning after December 15, 2019	Effective for fiscal years beginning after December 15, 2022
COVID-19 disrupted the mandatory adoption of CECL		
CARES Act (Mar 2020)	Allows banks to delay CECL adoption until the first day of the bank's fiscal year that begins after the date when the national emergency concerning the COVID-19 outbreak has ended	
Consolidated Appropriations Act (Dec 2020)	Allows banks to delay CECL adoption until the national emergency concerning the COVID-19 outbreak terminates, or January 1, 2022, whichever comes first	
Implications for our research: No bank was mandated to adopt CECL before January 1, 2022; banks that did so before January 1, 2022, were voluntary adopters.		

Appendix C: Variable definitions

Variable (in alphabetical order)	Definition
$ALW_{i,t-1}$	Loan loss reserves at the end of quarter $t-1$, scaled by total loans at the end of quarter $t-1$.
$CAPITAL_{i,t}$	Book value of equity at the end of quarter t, scaled by total assets at the end of quarter t.
$CAPITAL_{i,t-1}$	Book value of equity at the end of quarter $t-1$, scaled by total assets at the end of quarter $t-1$.
$CAPR1_{i,t}$	The tier-one risk-adjusted capital ratio at the end of quarter t.
$CECL_{i,t}$	An indicator variable that equals one for the quarter when banks adopt the current expected credit loss (CECL) model and all quarters after it, and zero otherwise.
$CECL\_HINDLOAN_{i,t}$	An indicator variable that equals one for the quarter when more-individual-loan banks adopt the CECL model and all quarters after it, and zero otherwise. We categorize CECL-adopting banks as more-individual-loan banks if they have a higher proportion of loans individually evaluated for impairment than the median value for the group of CECL-adopting banks. We measure this proportion as the pre-adoption average of loans individually evaluated for impairment ("bhckm746") divided by total loans ("bhck2122"), as in Beatty and Liao (2021). The pre-adoption period refers to the period that starts from the fourth quarter of 2018 and ends on the quarter before the CECL-adoption quarter.
$CECL\_HRISK_{i,t}$	An indicator variable that equals one for the quarter when high-risk-taking banks adopt the CECL model and all quarters after it, and zero otherwise. We categorize a CECL-adopting bank as high-risk-taking if its risk-taking in the pre-adoption period is greater than the median value for the group of CECL-adopting banks. We measure risk-taking as the Z-score in the pre-adoption period. The Z-score = (-1)×ln [(Avg(ROA)+Avg(Capital ratio)/σ(ROA)]. σ(ROA) is the standard deviation of ROA in the pre-adoption period, and Avg(ROA) is the average ROA ratio in the pre-adoption period, where ROA = net income / lagged total assets. Avg(Capital ratio) is the average capital ratio in the pre-adoption period, where Capital ratio = book value of equity / total assets.
$CECL\_LINDLOAN_{i,t}$	An indicator variable that equals one for the quarter when less-individual-loan banks adopt the CECL model and all quarters after it, and zero otherwise. We categorize CECL-adopting banks as less-individual-loan banks if they have a lower proportion of loans individually evaluated for impairment than the median value for the group of CECL-adopting banks.
$CECL\_LRISK_{i,t}$	An indicator variable that equals one for the quarter when low-risk-taking banks adopt the CECL model and all quarters after it, and zero otherwise. We categorize a CECL-adopting bank as low-risk-taking if its risk-taking in the pre-adoption period is smaller than the median value for the group of CECL-adopting banks.
$CECL\_NOTRAN_{i,t}$	An indicator variable that equals one during and after the quarter when the CECL-adopting banks adopt the CECL model without the CECL transition provision, and zero otherwise.
$CECL\_NOTRAN\_HCAP_{i,t}$	An indicator variable that equals one during and after the quarter when the CECL-adopting banks adopt the CECL model without the CECL transition provision and having a high pre-adoption capital ratio, and zero otherwise. A high pre-adoption capital ratio means that the CECL-adopting bank's tier-one risk-adjusted capital ratio in the quarter before CECL-adoption quarter is higher than the median value for the group of CECL-adopting banks.

$CECL\_NOTRAN\_LCAP_{i,t}$	An indicator variable that equals one during and after the quarter when the CECL-adopting banks adopt the CECL model without the CECL transition provision and having a low pre-adoption capital ratio, and zero otherwise. A low pre-adoption capital ratio means that the CECL-adopting bank's tier-one risk-adjusted capital ratio in the quarter before the CECL-adoption quarter is lower than the median value for the group of CECL-adopting banks.
$CECL\_POST1_{i,t}$	An indicator variable that equals one for the quarter when banks adopt the CECL model, and zero otherwise.
$CECL\_POST2+_{i,t}$	An indicator variable that equals one after the quarter when banks adopt the CECL model, and zero otherwise.
$CECL\_PRE1_{i,t}$	An indicator variable that equals one for the quarter before the CECL-adoption quarter, and zero otherwise.
$CECL\_TRAN_{i,t}$	An indicator variable that equals one during and after the quarter when the CECL-adopting banks adopt the CECL model with the CECL transition provision, and zero otherwise.
$CECL\_TRAN\_HCAP_{i,t}$	An indicator variable that equals one during and after the quarter when the CECL-adopting banks adopt the CECL model with the CECL transition provision and having a high pre-adoption capital ratio, and zero otherwise.
$CECL\_TRAN\_LCAP_{i,t}$	An indicator variable that equals one during and after the quarter when the CECL-adopting banks adopt the CECL model with the CECL transition provision and having a low pre-adoption capital ratio, and zero otherwise.
$DEPOSIT_{i,t-1}$	Total deposits in quarter t – 1, scaled by the total loans in quarter t – 1.
$EBP_{i,t}$	Earnings before loan loss provision in quarter t, scaled by the lagged total loans, multiplied by 100.
$EBP_{i,t-1}$	Earnings before loan loss provision in quarter t – 1, scaled by the lagged total loans, multiplied by 100.
$GDPGROWTH_{i,t}$	The percentage change in GDP from quarters t – 1 to t.
$LLP_{i,t}$	The loan loss provision in quarter t, scaled by the lagged total loans, multiplied by 100.
$LLRT1_{i,pre}$	The stock measure of loan loss recognition timeliness in the quarter before the CECL-adoption quarter. We calculate the stock measure as the loan loss reserves at quarter t divided by the nonperforming loans at quarter t (Beatty and Liao, 2011). A higher value indicates more timely loan loss recognition.
$LLRT2_{i,pre}$	The flow measure of loan loss recognition timeliness in the quarter before the CECL-adoption quarter. We follow Beatty and Liao (2011) to estimate two regression models on loan loss provisions for each bank-quarter using the observations of the past three years. We calculate the flow measure as the adjusted R^2 from regression model (b) minus the adjusted R^2 from regression model (a). The two regression models are as follows: (a) $LLP_t = \alpha_0 + \alpha_1 \Delta NPL_{t-2} + \alpha_2 \Delta NPL_{t-1} + \alpha_3 \, Capital\ R1_t + \alpha_4 \, EBP_t + \varepsilon_t$. (b) $LLP_t = \alpha_0 + \alpha_1 \Delta NPL_{t-2} + \alpha_2 \Delta NPL_{t-1} + \alpha_3 \Delta NPL_t + \alpha_4 \Delta NPL_{t+1} + \alpha_5 \, Capital\ R1_t + \alpha_6 \, EBP_t + \varepsilon_t$. $Capital\ R1_t$ is the tier-one risk-adjusted capital ratio at the beginning of the quarter, divided by 100. A higher flow measure indicates more timely loan loss recognition.

$LLRT3_{i,pre}$	The market measure (C-Score) of loan loss recognition timeliness in the quarter before the CECL-adoption quarter. To construct this measure, we follow Khan and Watts (2009) to estimate the annual cross-sectional model and calculate it as $\lambda_1+\lambda_2 SIZE_i+\lambda_3 MB_i+\lambda_4 LEV_i$. The regression model is as follows: $NI_i = \beta_0 + \beta_1 D_i + Returns_i \times (\mu_1 + \mu_2 SIZE_i + \mu_3 MB_i + \mu_4 LEV_i) + D_i \times Returns_i \times (\lambda_1 + \lambda_2 SIZE_i + \lambda_3 MB_i + \lambda_4 LEV_i) + (\delta_1 SIZE_i + \delta_2 MB_i + \delta_3 LEV_i + \delta_4 D_i \times SIZE_i + \delta_5 D_i \times MB_i + \delta_6 D_i \times LEV_i) + \varepsilon_t$. In the above model, NI_i is the net income divided by the lagged market value of equity. $Returns_i$ is the quarterly returns compounded from the monthly returns beginning the month after the fiscal quarter end. D_i is an indicator variable that equals 1 for negative returns, and zero otherwise. $SIZE_i$ is the logarithm of the market value of equity. MB_i is the ratio of the market value of equity to the book value of equity. LEV_i is the ratio of the book value of long-term debt divided by the market value of equity. A higher value of this variable indicates more timely loan loss recognition.
$NIM_{i,t-1}$	The net interest margin in quarter $t-1$. Net interest margin is computed by dividing the net tax-equivalent interest income by the average interest earning assets.
$NPL_{i,t-3}$	Nonperforming loans in quarter $t-3$, scaled by the total loans in quarter $t-4$, multiplied by 100.
$PSEUDO\_CECL_{i,t}$	An indicator variable that equals one for the quarter when the pseudo adopters adopt the CECL model and all quarters after it, and zero otherwise. The pseudo adopters are randomly selected from all banks, and the distribution of the pseudo adopters is the same as that of the actual CECL model adopters.
$ROE_{i,pre}$	The ratio of net income to the lagged book value of equity in the quarter before the CECL-adoption quarter.
$SIZE_{i,pre}$	The natural logarithm of total assets in the quarter before the CECL-adoption quarter.
$SIZE_{i,t}$	The natural logarithm of total assets in quarter t.
$SIZE_{i,t-1}$	The natural logarithm of total assets in quarter $t-1$.
$\Delta ALW_{i,day\text{-}one}$	The day-one adjustment to the loan loss allowance when banks adopt the CECL model divided by the lagged loan loss allowance. Data source: FR Y-9C reports compiled by the Federal Reserve Bank of Chicago.
$\Delta COVID19_{i,t}$	The change in bank-level COVID-19 exposure from quarters $t-1$ to t. COVID-19 exposure is measured as the frequency with which synonyms for COVID-19 are mentioned in the conference calls, scaled by the call length (Hassan et al., 2021). The variable is multiplied by 100.
$\Delta LOAN_{i,pre}$	The change in total loans in the quarter before the CECL-adoption quarter, scaled by the lagged total loans.
$\Delta LOAN_{i,t}$	The change in total loans from quarters $t-1$ to t, scaled by the total loans in quarter $t-1$.
$\Delta LOAN_{i,t+1}$	The change in total loans from quarters t to $t+1$, scaled by the total loans in quarter t.
$\Delta NPL_{i,pre}$	The change in nonperforming loans in the quarter before the CECL-adoption quarter, scaled by the lagged total loans. The variable is multiplied by 100.
$\Delta NPL_{i,t}$	The change in nonperforming loans from quarters $t-1$ to t, scaled by the total loans in quarter $t-1$. The variable is multiplied by 100.
$\Delta NPL_{i,t+1}$	The change in nonperforming loans from quarters t to $t+1$, scaled by the total loans in quarter t. The variable is multiplied by 100.
$\Delta NPL_{i,t+2}$	The change in nonperforming loans from quarters $t+1$ to $t+2$, scaled by the total loans in quarter $t+1$. The variable is multiplied by 100.

$\Delta NPL_{i,t-1}$	The change in nonperforming loans from quarters $t-2$ to $t-1$, scaled by the total loans in quarter $t-2$. The variable is multiplied by 100.
$\Delta NPL_{i,t-2}$	The change in nonperforming loans from quarters $t-3$ to $t-2$, scaled by the total loans in quarter $t-3$. The variable is multiplied by 100.

Figures

Figure 1 Bank distribution

This figure shows the status of a bank's current expected credit loss (CECL) model adoption and whether the bank elects to use the CECL transition provision.

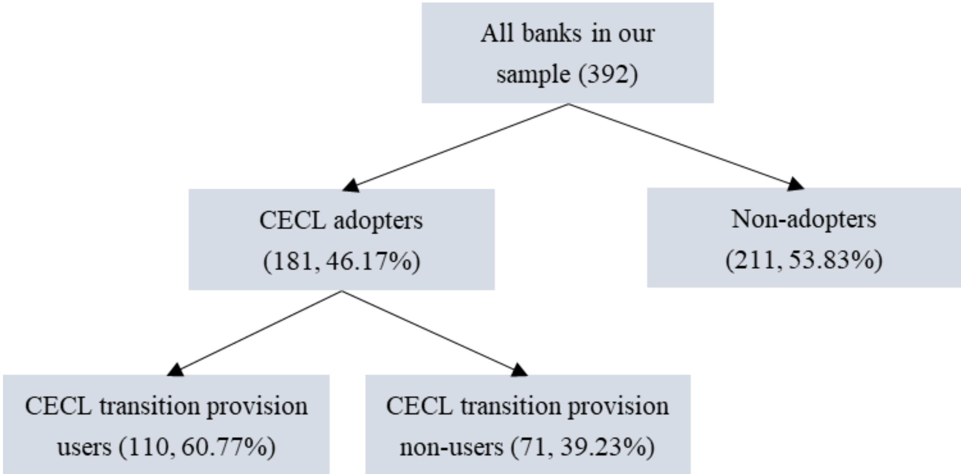
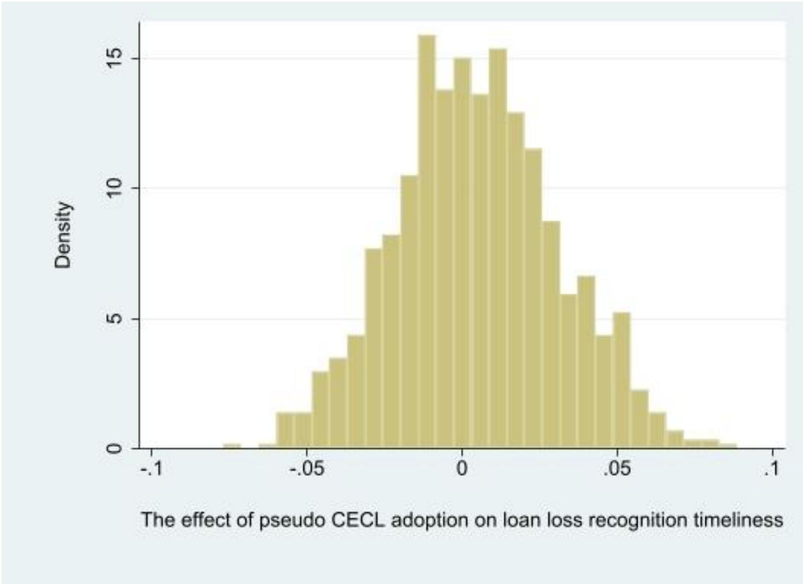


Figure 2 Placebo tests

This figure shows the empirical distribution of the coefficient on $PSEUDO\_CECL_{i,t} \times \Delta NPL_{i,t+1}$ across 1,000 estimations of Equation (1) in which we replace actual current expected credit loss (CECL) model adopters with pseudo adopters. Pseudo adopters are randomly selected from all banks, and their distribution is the same as that of the actual adopters. The average value of the coefficient on $PSEUDO\_CECL_{i,t} \times \Delta NPL_{i,t+1}$ across 1,000 estimations is 0.0048.



Tables

Table 1 Sample distribution

This table presents the sample distribution by quarter.

Calendar quarter	Banks that do not adopt the CECL model	Banks that adopt the CECL model	Total number of banks	Percentage of banks that adopt the CECL model	Banks that adopt the CECL model in the current quarter
2018Q4	364	0	364	0.00%	0
2019Q1	362	0	362	0.00%	0
2019Q2	370	0	370	0.00%	0
2019Q3	371	0	371	0.00%	0
2019Q4	375	0	375	0.00%	0
2020Q1	236	137	373	36.73%	137
2020Q2	240	137	377	36.34%	0
2020Q3	235	141	376	37.50%	4
2020Q4	218	159	377	42.18%	18
2021Q1	193	178	371	47.98%	22
Total	2,964	752	3,716	20.24%	181

Table 2 Descriptive statistics

This table presents the mean, standard deviation (SD), 25th percentile (P25), median, and 75th percentile (P75) of the variables used in our baseline regression. Our sample period covers 2018Q4 to 2021Q1, and the final sample consists of 3,716 bank-quarter observations. Variable definitions are summarized in Appendix C. All continuous variables are winsorized at the 1st and 99th percentiles.

Variable	Mean	SD	P25	Median	P75
$LLP_{i,t}$	0.0837	0.1361	0.0110	0.0447	0.1100
$CECL_{i,t}$	0.2024	0.4018	0.0000	0.0000	0.0000
$\Delta NPL_{i,t+1}$	0.0095	0.2034	–0.0672	–0.0073	0.0609
$\Delta NPL_{i,t}$	0.0141	0.2075	–0.0657	–0.0043	0.0660
$\Delta NPL_{i,t-1}$	0.0178	0.2087	–0.0618	–0.0022	0.0682
$\Delta NPL_{i,t-2}$	0.0154	0.2018	–0.0609	–0.0026	0.0662
$NPL_{i,t-3}$	0.8397	0.6983	0.3941	0.6433	1.0624
$SIZE_{i,t}$	8.3275	1.5259	7.1906	8.0537	9.1839
$CAPITAL_{i,t}$	0.1117	0.0259	0.0936	0.1086	0.1255
$EBP_{i,t}$	0.5733	0.2776	0.4192	0.5552	0.6936
$\Delta LOAN_{i,t}$	0.0250	0.0602	–0.0037	0.0118	0.0314

Table 3 Baseline analysis: The effect of the CECL model on loan loss recognition timeliness

This table presents the results of the effect of the CECL model on loan loss recognition timeliness. Column 1 (2) shows the results of the baseline regression (parallel trend test). The dependent variable is $LLP_{i,t}$, calculated as the loan loss provision in quarter t, scaled by the lagged total loans. $CECL_{i,t}$ is an indicator variable that equals one for the quarter when banks adopt the CECL model and all quarters after it, and zero otherwise. $\Delta NPL_{i,t+1}$ is the change in nonperforming loans from quarters t to $t + 1$, scaled by the total loans in quarter t. $CECL\_PRE1_{i,t}$ is an indicator variable that equals one in the quarter before the CECL adoption quarter, and zero otherwise. $CECL\_POST1_{i,t}$ ($CECL\_POST2+_{i,t}$) is an indicator variable that equals one in (after) the quarter when banks adopt the CECL model, and zero otherwise. Other variable definitions are presented in Appendix C. Models are estimated using OLS regressions. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Dep. Var. = $LLP_{i,t}$	(1) Baseline regression	(2) Parallel trend test
$CECL_{i,t} \times \Delta NPL_{i,t+1}$	0.1421***	
	(5.95)	
$CECL_{i,t}$	0.0343***	
	(5.28)	
$CECL\_PRE1_{i,t} \times \Delta NPL_{i,t+1}$		–0.0258
		(–0.66)
$CECL\_POST1_{i,t} \times \Delta NPL_{i,t+1}$		0.1237***
		(2.60)
$CECL\_POST2+_{i,t} \times \Delta NPL_{i,t+1}$		0.1109***
		(4.27)
$CECL\_PRE1_{i,t}$		–0.0060
		(–0.62)
$CECL\_POST1_{i,t}$		0.1195***
		(12.56)
$CECL\_POST2+_{i,t}$		–0.0060
		(–0.80)
$\Delta NPL_{i,t+1}$	–0.0041	0.0045
	(–0.43)	(0.47)
$\Delta NPL_{i,t}$	0.0422***	0.0413***
	(4.56)	(4.56)
$\Delta NPL_{i,t-1}$	0.0173*	0.0187**
	(1.86)	(2.05)
$\Delta NPL_{i,t-2}$	0.0101	0.0111
	(1.02)	(1.15)
$NPL_{i,t-3}$	0.0176**	0.0203***
	(2.26)	(2.67)
$SIZE_{i,t}$	0.0347*	0.0406**
	(1.66)	(1.99)
$CAPITAL_{i,t}$	–0.8451***	–0.8431***
	(–3.32)	(–3.39)
$EBP_{i,t}$	0.1061***	0.0968***
	(9.31)	(8.66)
$\Delta LOAN_{i,t}$	0.1553***	0.1389***
	(4.60)	(4.21)
Constant	–0.1981	–0.2418
	(–1.08)	(–1.35)
Bank FE & Quarter FE	Yes	Yes
N	3,716	3,716
Adj. R^2	0.477	0.501

Table 4 Robustness tests

This table shows the results of the robustness tests. Panel A presents the results for alternative measures of loan loss recognition timeliness. The dependent variable is $LLP_{i,t}$, calculated as the loan loss provision in quarter t, scaled by the lagged total loans. $CECL_{i,t}$ is an indicator variable that equals one for the quarter when banks adopt the CECL model and all quarters after it, and zero otherwise. $\Delta NPL_{i,t+1}$ is the change in nonperforming loans from quarters t to t + 1, scaled by the total loans in quarter t. $\Delta NPL_{i,t+2}$ is the change in nonperforming loans from quarters t + 1 to t + 2, scaled by the total loans in quarter t + 1. $GDPGROWTH_{i,t}$ is the percentage change in GDP from quarters t – 1 to t. $\Delta COVID19_{i,t}$ is the change in bank-level COVID-19 exposure from quarters t – 1 to t. COVID-19 exposure is measured as the frequency with which synonyms for COVID-19 are mentioned in the conference calls, scaled by the call length. Panel B presents the results for alternative samples. In Column 1 (2), we keep banks that adopt the CECL model in (after) the first quarter of 2020 and banks that do not adopt during our sample period. The coefficients on the control variables and constants are omitted. Panel C shows the results from using a recently developed test by Oster (2019) to evaluate the sensitivity of the results to unobservable selection and coefficient stability. Column 1 shows the results estimated from the model without controls, in which we keep only $CECL_{i,t} \times \Delta NPL_{i,t+1}$, $CECL_{i,t}$, and $\Delta NPL_{i,t+1}$. Column 2 shows the results estimated from the model with all controls. The models are estimated using OLS regressions. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Panel A: Alternative measures of loan loss recognition timeliness

Dep. Var. = $LLP_{i,t}$	(1)	(2)	(3)
$CECL_{i,t} \times \Delta NPL_{i,t+1}$	0.1362***		
	(5.22)		
$CECL_{i,t} \times \Delta NPL_{i,t+2}$	0.1854***		
	(6.92)		
$CECL_{i,t} \times GDPGROWTH_{i,t}$		–0.3226***	
		(–16.23)	
$CECL_{i,t} \times \Delta COVID19_{i,t}$			0.3692***
			(2.85)
Controls & Constant	Yes	Yes	Yes
Bank FE & Quarter FE	Yes	Yes	Yes
N	3,322	3,716	761
Adj. R^2	0.498	0.510	0.549

Panel B: Alternative samples

Dep. Var. = $LLP_{i,t}$	(1) CECL adopters in 2020Q1 versus non-adopters	(2) CECL adopters after 2020Q1 versus non-adopters
$CECL_{i,t} \times \Delta NPL_{i,t+1}$	0.1394***	0.1530**
	(5.49)	(2.20)
Controls & Constant	Yes	Yes
Bank FE & Quarter FE	Yes	Yes
N	3,277	2,337
Adj. R^2	0.466	0.426

Panel C: Unobservable selection and coefficient stability

	(1) Model without controls	(2) Model with controls
Coefficient on $CECL_{i,t} \times \Delta NPL_{i,t+1}$	0.2102	0.1421
R^2	0.064	0.535
Max. R^2	0.695	
δ	4.472	

Table 5 Cross-sectional variation with incurred credit loss (ICL) constraints

This table presents the results for the cross-sectional variations with the ICL constraints. The dependent variable is $LLP_{i,t}$, calculated as the loan loss provision in quarter *t*, scaled by the lagged total loans. $\Delta NPL_{i,t+1}$ is the change in nonperforming loans from quarters *t* to *t* + 1, scaled by the total loans in quarter *t*. $CECL\_HRISK_{i,t}$ ($CECL\_LRISK_{i,t}$) is an indicator variable that equals one for the quarter when high-risk-taking (low-risk-taking) banks adopt the current expected credit loss (CECL) model and all quarters after it, and zero otherwise. We categorize CECL-adopting banks as high (low) risk-taking banks if their risk-taking is greater (smaller) than the median value for the group of CECL-adopting banks. We measure risk-taking as the Z-score in the pre-adoption period. The Z-score = (-1) × ln [(Avg(ROA) + Avg(Capital ratio) / σ(ROA)]. σ(ROA) is the standard deviation of ROA in the pre-adoption period, and Avg(ROA) is the average ROA ratio in the pre-adoption period, where ROA = net income / lagged total assets. Avg(Capital ratio) is the average capital ratio in the pre-adoption period, where Capital ratio = book value of equity / total assets. $CECL\_HINDLOAN_{i,t}$ ($CECL\_LINDLOAN_{i,t}$) is an indicator variable that equals one for the quarter when more-individual-loan (less-individual-loan) banks adopt the CECL model and all quarters after it, and zero otherwise. We categorize CECL-adopting banks as more-individual-loan (less-individual-loan) banks if they have a higher (lower) proportion of loans individually evaluated for impairment than the median value for the group of CECL-adopting banks. We measure this proportion as the pre-adoption average of loans individually evaluated for impairment ("bhckm746") divided by total loans ("bhck2122"), as in Beatty and Liao (2021). See Appendix C for other variable definitions. The models are estimated using OLS regressions. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Dep. Var. = $LLP_{i,t}$	(1)	(2)
$CECL\_HRISK_{i,t} \times \Delta NPL_{i,t+1}$ [A]	0.2126***	
	(6.35)	
$CECL\_LRISK_{i,t} \times \Delta NPL_{i,t+1}$ [B]	0.0741**	
	(2.36)	
$CECL\_HRISK_{i,t}$	0.0216***	
	(2.59)	
$CECL\_LRISK_{i,t}$	0.0479***	
	(5.99)	
$CECL\_HINDLOAN_{i,t} \times \Delta NPL_{i,t+1}$ [C]		0.1677***
		(5.67)
$CECL\_LINDLOAN_{i,t} \times \Delta NPL_{i,t+1}$ [D]		0.0813**
		(2.01)
$CECL\_HINDLOAN_{i,t}$		0.0288***
		(3.46)
$CECL\_LINDLOAN_{i,t}$		0.0427***
		(5.16)
$\Delta NPL_{i,t+1}$	–0.0044	–0.0028
	(–0.46)	(–0.30)
$\Delta NPL_{i,t}$	0.0422***	0.0430***
	(4.56)	(4.68)
$\Delta NPL_{i,t-1}$	0.0171*	0.0189**
	(1.84)	(2.05)
$\Delta NPL_{i,t-2}$	0.0104	0.0100
	(1.06)	(1.03)
$NPL_{i,t-3}$	0.0178**	0.0147*
	(2.30)	(1.91)
$SIZE_{i,t}$	0.0299	0.0241
	(1.43)	(1.16)
$CAPITAL_{i,t}$	–0.8814***	–0.9582***
	(–3.47)	(–3.76)
$EBP_{i,t}$	0.1095***	0.1143***
	(9.61)	(10.03)

$\Delta LOAN_{i,t}$	0.1548***	0.1452***
	(4.60)	(4.36)
Constant	–0.1569	–0.1001
	(–0.86)	(–0.55)
Bank FE & Quarter FE	Yes	Yes
N	3,716	3,653
Adj. R^2	0.479	0.473
p-value of testing the difference between coefficients on [A] and [B]:	0.0017***	
p-value of testing the difference between coefficients on [C] and [D]:		0.0732*

Table 6 Cross-sectional variation with use of the current expected credit loss (CECL) transition provision

Panel A presents the results of the impact of the CECL model on regulatory capital. The dependent variable in Columns 1 and 2 is $CAPR1_{i,t}$, measured as the tier-one risk-adjusted capital ratio at the end of quarter t. $CECL_{i,t}$ is an indicator variable that equals one for the quarter when banks adopt the CECL model and all quarters after it, and zero otherwise. $CECL\_TRAN_{i,t}$ ($CECL\_NOTRAN_{i,t}$) is an indicator variable that equals one during and after the quarter when the CECL-adopting banks adopt the CECL model with (without) the CECL transition provision, and zero otherwise. Panel B presents the results for cross-sectional variations in CECL transition provision. The dependent variable is $LLP_{i,t}$, calculated as the loan loss provision in quarter t, scaled by the lagged total loans. $\Delta NPL_{i,t+1}$ is the change in nonperforming loans from quarters t to t + 1, scaled by the total loans in quarter t. $CECL\_TRAN\_LCAP_{i,t}$ ($CECL\_NOTRAN\_LCAP_{i,t}$) is an indicator variable that equals one during and after the quarter when the CECL-adopting banks adopt the CECL model with (without) the CECL transition provision and having a low pre-adoption capital ratio, and zero otherwise. $CECL\_TRAN\_HCAP_{i,t}$ ($CECL\_NOTRAN\_HCAP_{i,t}$) is an indicator variable that equals one during and after the quarter when the CECL-adopting banks adopt the CECL model with (without) the CECL transition provision and having a high pre-adoption capital ratio, and zero otherwise. Appendix C provides definitions for the other variables. The models are estimated using OLS regressions. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Panel A: Effect of switching to the CECL model on regulatory capital

Dep. Var. = $CAPR1_{i,t}$	(1)	(2)
$CECL_{i,t}$	–0.0011*	
	(–1.75)	
$CECL\_TRAN_{i,t}$ [A]		–0.0007
		(–0.91)
$CECL\_NOTRAN_{i,t}$ [B]		–0.0018**
		(–2.09)
$\Delta NPL_{i,t}$	–0.0018**	–0.0018**
	(–2.24)	(–2.24)
$\Delta NPL_{i,t-1}$	–0.0011	–0.0011
	(–1.31)	(–1.30)
$\Delta NPL_{i,t-2}$	–0.0021**	–0.0020**
	(–2.37)	(–2.35)
$NPL_{i,t-3}$	–0.0005	–0.0005
	(–0.72)	(–0.65)
$SIZE_{i,t-1}$	–0.0175***	–0.0176***
	(–9.98)	(–10.03)
$EBP_{i,t-1}$	0.0036***	0.0036***
	(3.63)	(3.65)
$ALW_{i,t-1}$	0.4657***	0.4461***
	(5.87)	(5.51)
Constant	0.2668***	0.2679***
	(18.14)	(18.18)
Bank FE & Quarter FE	Yes	Yes
N	3509	3509
Adj. R^2	0.872	0.872
p–value of testing the difference between coefficients on [A] and [B]:		0.2361

Panel B: Cross-sectional variation with CECL transition provision

Dep. Var. = $LLP_{i,t}$	(1)	(2)
$CECL\_TRAN_{i,t} \times \Delta NPL_{i,t+1}$ [A]	0.1855***	
	(6.62)	
$CECL\_NOTRAN_{i,t} \times \Delta NPL_{i,t+1}$ [B]	0.0422	
	(1.05)	
$CECL\_TRAN_{i,t}$	0.0419***	
	(5.63)	
$CECL\_NOTRAN_{i,t}$	0.0181*	
	(1.92)	
$CECL\_TRAN\_LCAP_{i,t} \times \Delta NPL_{i,t+1}$ [C]		0.1743***
		(5.18)
$CECL\_NOTRAN\_LCAP_{i,t} \times \Delta NPL_{i,t+1}$ [D]		–0.0304
		(–0.57)
$CECL\_TRAN\_HCAP_{i,t} \times \Delta NPL_{i,t+1}$ [E]		0.1986***
		(4.24)
$CECL\_NOTRAN\_HCAP_{i,t} \times \Delta NPL_{i,t+1}$ [F]		0.1319**
		(2.24)
$CECL\_TRAN\_LCAP_{i,t}$		0.0571***
		(6.11)
$CECL\_NOTRAN\_LCAP_{i,t}$		0.0292**
		(2.15)
$CECL\_TRAN\_HCAP_{i,t}$		0.0247**
		(2.49)
$CECL\_NOTRAN\_HCAP_{i,t}$		0.0079
		(0.64)
$\Delta NPL_{i,t+1}$	–0.0043	–0.0037
	(–0.45)	(–0.39)
$\Delta NPL_{i,t}$	0.0412***	0.0413***
	(4.45)	(4.47)
$\Delta NPL_{i,t-1}$	0.0169*	0.0168*
	(1.82)	(1.81)
$\Delta NPL_{i,t-2}$	0.0099	0.0090
	(1.00)	(0.91)
$NPL_{i,t-3}$	0.0170**	0.0153*
	(2.18)	(1.96)
$SIZE_{i,t}$	0.0374*	0.0358*
	(1.79)	(1.71)
$CAPITAL_{i,t}$	–0.8136***	–0.7848***
	(–3.20)	(–3.08)
$EBP_{i,t}$	0.1058***	0.1050***
	(9.30)	(9.23)
$\Delta LOAN_{i,t}$	0.1577***	0.1587***
	(4.68)	(4.71)
Constant	–0.2241	–0.2119
	(–1.22)	(–1.15)
Bank FE & Quarter FE	Yes	Yes
N	3,716	3,710
Adj. R^2	0.479	0.480
p-value of testing the difference between coefficients on [A] and [B]:	0.0024***	
p-value of testing the difference between coefficients on [C] and [D]:		0.0009***
p-value of testing the difference between coefficients on [E] and [F]:		0.3685

Table 7 Loan loss recognition timeliness during the incurred credit loss (ICL) regime and the cumulative-effect adjustment to the loan loss allowance upon adoption of the current expected credit loss (CECL) model

This table presents the results of the impact of pre-adoption loan loss recognition on the cumulative-effect adjustment to the loan loss allowance after adopting the CECL model. The CECL model requires banks to use a modified-retrospective transition approach to deal with the opening balances of loan loss reserves, as the reserves must reflect the use of CECL to account for prior-period reserves. The dependent variable is $\Delta ALW_{i,day\text{-}one}$, calculated as the day-one adjustment to the loan loss allowance when banks adopt the CECL model divided by the lagged loan loss allowance. The independent variable is the loan loss recognition timeliness in the quarter before the CECL-adoption quarter. We have three proxies for pre-adoption loan loss recognition timeliness: $LLRT1_{i,pre}$, $LLRT2_{i,pre}$, and $LLRT3_{i,pre}$. Appendix C provides definitions for the other variables. The models are estimated using OLS regressions. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Dep. Var. = $\Delta ALW_{i,day\text{-}one}$	(1)	(2)	(3)
$LLRT1_{i,pre}$	–0.0158*		
	(–1.94)		
$LLRT2_{i,pre}$		–0.0939	
		(–0.79)	
$LLRT3_{i,pre}$			–0.4968**
			(–2.18)
$SIZE_{i,pre}$	0.0239	0.0328	–0.0375
	(0.76)	(1.01)	(–0.80)
$\Delta LOAN_{i,pre}$	1.6567***	1.6510***	1.7892***
	(3.12)	(3.03)	(3.25)
$\Delta NPL_{i,pre}$	–0.1146	–0.1215	0.0168
	(–0.41)	(–0.40)	(0.05)
$ROE_{i,pre}$	–5.4515	–6.4352	1.2249
	(–1.11)	(–1.28)	(0.19)
Constant	0.2503	0.1630	0.6232
	(0.81)	(0.51)	(1.57)
N	141	137	128
Adj. R^2	0.099	0.075	0.110

Table 8 Effect of switching to the current expected credit loss (CECL) model on bank lending

This table presents the results of the impact of the switch to the CECL model on bank lending. The dependent variable in Column 1 (2) is $\Delta LOAN_{i,t}$ ($\Delta LOAN_{i,t+1}$). $\Delta LOAN_{i,t}$ is the change in total loans from quarters $t - 1$ to t, scaled by the total loans in quarter $t - 1$. $\Delta LOAN_{i,t+1}$ is the change in total loans from quarters t to $t + 1$, scaled by the total loans in quarter t. $CECL_{i,t}$ is an indicator variable that equals one for the quarter when banks adopt the CECL model and all quarters after it, and zero otherwise. Appendix C provides definitions for the other variables. The models are estimated using OLS regressions. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	(1)	(2)
Dep. Var. =	$\Delta LOAN_{i,t}$	$\Delta LOAN_{i,t+1}$
$CECL_{i,t}$	–0.0069**	–0.0113***
	(–2.08)	(–3.35)
$\Delta NPL_{i,t}$	0.0270***	–0.0126***
	(5.98)	(–2.74)
$\Delta NPL_{i,t-1}$	–0.0001	–0.0066
	(–0.02)	(–1.41)
$\Delta NPL_{i,t-2}$	0.0027	–0.0015
	(0.54)	(–0.30)
$NPL_{i,t-3}$	0.0038	–0.0073*
	(0.99)	(–1.84)
$SIZE_{i,t-1}$	–0.1699***	–0.1441***
	(–16.53)	(–13.80)
$CAPITAL_{i,t-1}$	0.0604	0.0121
	(0.48)	(0.09)
$EBP_{i,t-1}$	0.0084	0.0068
	(1.41)	(1.13)
$DEPOSIT_{i,t-1}$	0.0558***	0.0844***
	(4.09)	(6.09)
$NIM_{i,t-1}$	–0.0111**	–0.0055
	(–2.20)	(–1.06)
Constant	1.3955***	1.1417***
	(14.64)	(11.80)
Bank FE & Quarter FE	Yes	Yes
N	3,697	3,697
Adj. R^2	0.314	0.290