Current Expected Credit Losses (CECL) Standard and Banks' Information Production[*]

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This version: October 2022

Abstract

We examine whether the adoption of the current expected credit losses (CECL) model, which reflects forward-looking information in loan loss provisions (LLP), improves banks' information production. Consistent with better information production, we test and find changes in CECL banks' financial reporting and operations. First, these banks' loan loss provisions become timelier and better reflect future local economic conditions. Second, CECL banks disclose longer, more forward-looking, and more quantitative LLP information. Lastly, they have fewer loan defaults after adopting CECL. The improvements in information production are greater for banks that invest more in CECL-related information systems and human capital. Our findings suggest that banks benefit from better information quality by adopting a more forward-looking accounting standard.

Keywords: Current Expected Credit Losses (CECL); Banks; Information Production; Loan Loss Provisioning

JEL Classification: E32, G21, G28, M41, M48

[*]We thank Matthias Breuer, João Granja (discussant), Shiva Rajgopal, Cindy Vojtech, James Wang, Teng Wang, and the workshop participants at Columbia University, the Federal Reserve Board, and the 2022 Federal Reserve Stress Testing Research Conference for their helpful comments and suggestions. The views expressed in this study are those of the authors and do not necessarily reflect the views of the Federal Reserve Board or the Federal Reserve System. We are grateful to Jeffrey Jou, Fanqi Liu, Cong Xiao, and Bohyun Yang for excellent research assistance. We thank our respective institutions for research funding. All errors are our own.

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1 Introduction

In response to the financial crisis of 2007–2009, the Financial Accounting Standards Board (FASB) replaced the incurred loss model (ILM) for estimating credit losses with the current expected credit losses (CECL) model.[1] The adoption of the CECL model is considered to be one of the most important accounting standard changes for U.S. banks (ABA, 2016) and is expected to significantly impact banks' financial reporting, compliance, and operating decisions. The CECL approach fundamentally changes the way banks evaluate and provision for credit losses because they have to provision for all *expected* credit losses on all outstanding loans over their entire remaining lives, as opposed to only *incurred* losses under the ILM. Extending the estimation of provisions to the remaining loan lives requires banks to generate reasonable and supportable forecasts of future economic conditions and factor the impacts of these changing dynamics into their reported loan loss provisions (LLPs).

In this paper, we examine whether CECL adoption affects banks' information production and investigate the potential channels through which these effects might arise.[2] Prior studies show that banks' information sets affect their reporting choices and operating decisions (Leland and Pyle, 1977; Diamond, 1984; Qian et al., 2015; Khan and Ozel, 2016; Lisowsky et al., 2017; Howes and Weitzner, 2021; Bertomeu et al., 2022). Thus, understanding the impact of CECL adoption on banks' information production processes provides insights into how and why the CECL approach could affect banks' financial reporting and operational decision-making (e.g., risk management). We hypothesize that CECL-adopting banks would improve their information production because CECL adoption requires incorporating more forward-looking information and forecasts of economic conditions. As information production is not directly observable, we instead examine how CECL adoption affects banks' LLP

[1] Accounting Standards Update (ASU) 2016-13 (ASC 326) is issued on June 16, 2016 (*link*). The new standard is set to take effect on January 1, 2020 (2023) for large public (small public and private) firms.

[2] We define the information production process as banks' collection, analysis, organization, and reporting of information relevant to their loan portfolios.

recognition, disclosures, and credit risk management.

While banks are expected to exert more effort to collect, analyze, organize, and report information relevant to their loan portfolios under the CECL approach, such effects may not be salient. In particular, CECL adoption may not improve the quality of reporting and operating decisions for the following reasons. First, implementing CECL is costly because forecasting the future is inherently challenging. Industry experts have commented that the cost of CECL implementation is high, especially for smaller banks with resource constraints (Stein, 2018; McWilliams, 2020). Second, banks often have inefficient or disjointed information systems due to mergers and acquisitions and geographic dispersion of branches. Thus, useful information on borrowers' credit profiles often resides with loan officers and is not shared through an internal information system (Stein, 2002; Hertzberg et al., 2010). Finally, the CECL approach allows management more discretion and judgment in estimating LLP than the ILM (Walker, 2019; Kim, 2022). Thus, if banks had incentives to exploit the ILM opportunistically, they may exercise even more discretion under the CECL approach, resulting in no improvements to their reporting and operating decisions. Hence, whether CECL adoption improves banks' information production processes is an empirical question.

We study the impact of CECL adoption using U.S. bank holding companies (BHCs) from 2017 to 2021. The sample includes three years prior to and two years after CECL implementation for large public banks. We employ a difference-in-differences research design and compare a treatment group of large public banks subject to CECL as of January 1, 2020, with a control group of small public banks and private banks not subject to CECL until 2023. To better identify the impact of CECL adoption, we exclude banks that delayed adopting CECL under the Coronavirus Aid, Relief, and Economic Security (CARES) Act exemption.[3]

[3]The CARES Act was signed into law in March 2020, allowing banks to delay adoption by the earlier of (1) the termination of COVID-19 national emergency or (2) January 1, 2022. In our final sample, among public banks subject to CECL as of January 1, 2020, 42 banks elected to delay CECL adoption. As of January 1, 2022, all these banks have adopted CECL, except for two banks that merged with another bank.

We begin our analyses by examining the properties of banks' LLPs. If CECL adoption improves banks' information production, we expect the most salient impact to manifest in LLPs. First, we investigate whether CECL increases the timeliness of banks' LLPs. The CECL approach requires banks to incorporate forward-looking information when estimating their provisions. Therefore, if banks produce better information about their borrowers, they would quickly react to loan quality deterioration by recognizing LLPs accordingly. Second, we examine whether CECL adopters' LLPs contain more information about future local economic conditions. Prior studies find that banks' loan portfolios have helpful information about local economic conditions because they collect detailed and proprietary information about their customers' financial prospects (Khan and Ozel, 2016). Thus, if banks produce better information about their customers and economic conditions, we expect banks' LLPs to reflect future local economic conditions better after CECL adoption.

Consistent with CECL banks producing higher quality information, we find that they record LLPs in a timelier manner, and their LLPs reflect future local economic conditions better. These effects are stronger for heterogeneous loans (commercial real estate, construction, and commercial and industrial loans), which require more borrower-specific information to monitor than homogeneous loans (residential and consumer loans).

Next, we examine whether the impact of CECL adoption is manifested in banks' disclosures. Prior studies suggest firms' internal information environments significantly affect their disclosures (Dorantes et al., 2013; Ittner and Michels, 2017; Cheng et al., 2018). Hence, if banks produce better information for their loan portfolios, we expect managers of CECL banks to disclose more informative LLP-related information in their financial reports. Consistent with this prediction, we find that the LLP-related information in CECL adopters' annual SEC 10-K filings becomes longer and contains more forward-looking and quantitative information.

One potential concern regarding our LLP recognition and disclosure analyses is that we cannot distinguish between two mechanisms that could explain our findings. First, banks might already have all the information, and CECL adoption only changes banks' reporting behavior without affecting the remaining dimensions of their information production (i.e., the collection, analysis, and organization of information). Second, CECL adoption may prompt banks to exert more effort to produce forward-looking information about their customers and economic conditions. The second mechanism is arguably more intriguing as it involves *real* improvements in banks' information production activities. While these two mechanisms can coincide, and we do not refute the existence of the first mechanism, we examine whether the second mechanism plausibly explains our findings using the loan default analysis.

Prior studies suggest that monitoring borrowers is a significant part of banks' business models (Diamond, 1984; Rajan and Winton, 1995), and banks actively collect borrower information as part of their monitoring role (Gustafson et al., 2021). More information about borrowers also leads to fewer defaults on banks' loans due to better screening and monitoring (Ertan et al., 2017; Lisowsky et al., 2017). If banks screen and monitor loans better by using more forward-looking information, we expect CECL banks to observe fewer borrower defaults after CECL adoption. Importantly, fewer defaults are unlikely to be driven by changes in reporting behavior but can be plausibly explained by banks producing better information. However, a major concern for the default analysis is that borrower-specific credit risks or loan terms may drive loan default, and these characteristics are mostly unobservable to researchers. We overcome these challenges by controlling for borrower-specific credit risks and loan-level characteristics using confidential FR Y-14Q regulatory filings. Because only the largest banks report FR Y-14Q filings, for the loan-level default analysis, we use U.S. intermediate holding companies (IHCs) of foreign banks that adopted IFRS 9 in 2018 as the control group.[4] We find that CECL-adopting banks experience fewer loan defaults than IHCs after CECL adoption. These results are more salient for private borrowers and riskier loans, consistent with the impact of information production being more pronounced for more

[4]We cannot use a control sample of U.S. BHCs that have not adopted CECL because none of these banks report FR Y-14Q.

opaque and riskier borrowers (Gustafson et al., 2021).

A natural follow-up question is through what channel CECL banks improve their information production. Recent studies suggest that financial institutions are increasingly investing in information technology and hiring relevant experts to efficiently deal with regulatory monitoring, reporting, and compliance (Charoenwong et al., 2022). Thus, investment in information systems and human capital related to CECL adoption is a plausible channel for improved information production. We proxy for information systems and human capital investment using banks' job-postings data, following the approach in the literature (Hershbein and Kahn, 2018; Acemoglu et al., 2022).[5] We find that CECL-related job postings mainly contain three job functions: managerial positions related to managing relationships with customers, including collecting and evaluating customer-specific information; quantitative jobs requiring skills related to analyzing and processing the data; and auditing jobs requiring skills related to financial reporting. Thus, CECL-related positions are generally associated with banks' information production processes of collecting, analyzing, organizing, and reporting information. Consistent with our prediction, we find that CECL adopters posted significantly more jobs related to the CECL approach over the sample period than ILM banks.

Lastly, we conduct cross-sectional tests by separating CECL-adopting banks based on whether they made large or small investments in CECL-related information systems and human capital. We find that banks with more CECL-related job postings exhibit more significant improvements in their LLP recognition, disclosures, and credit risk management. Notably, these improvements are even more salient for larger banks. Overall, our analyses using the job posting data suggest that the investment in information systems and human

[5]Our underlying assumption is that the demand for human capital is closely associated with related-system investment following prior studies. For example, Hershbein and Kahn (2018) document that increased demand for labor skills is linked to IT capital investment. We acknowledge that banks can outsource CECL-related functions, including hiring consulting firms and purchasing credit models to prepare for CECL adoption. However, banks must also maintain internal systems and have dedicated staff to comply with the CECL approach in their daily operations. Therefore, CECL-related hiring is likely closely related to CECL-related IT investments.

capital is a plausible mechanism through which CECL adoption affects banks' information production. However, these investments seem to be more concentrated in larger banks, consistent with prior studies suggesting that larger banks have more resources to invest in technology and enjoy greater benefits because information creation, collection, and analyses have economies of scale (Wilson, 1975; Begenau et al., 2018; Charoenwong et al., 2022; Farboodi and Veldkamp, 2022).

Our study makes several contributions to the accounting, economics, and finance literature. First, we provide empirical evidence of the economic consequences of CECL adoption, which is useful to standard setters. Several concurrent studies examine the impact of CECL adoption on lending procyclicality (e.g., Cohen and Edwards, 2017; Abad and Suarez, 2018; Covas and Nelson, 2018; Harris et al., 2018; Loudis and Ranish, 2019; Chae et al., 2020; Huber, 2021; Chen et al., 2022b; Lu and Nikolaev, 2022). Another stream of studies suggests that LLPs under the CECL model contain some decision-useful information (e.g., Beatty and Liao, 2021; Wheeler, 2021; Gee et al., 2022). Our paper complements these studies by documenting evidence that CECL adoption improves banks' information production. Specifically, we show that accounting standards incentivize banks to improve their reporting and operations by using better information about their borrowers and underlying economic conditions. In addition, our findings that banks invest into information systems and human capital to generate better information for lending decisions and monitoring suggest that CECL could provide further insights for evaluation of credit portfolios. In particular, information gains from CECL can be used to explore loss rates in stress testing or procedures for loan-portfolio bank examinations. Thus, our findings suggest that accounting standards could help bank supervision and regulation.

Our study also adds to the literature examining the effects of accounting standards on firms' information sets. Shroff (2017) finds that firms' investments are affected by GAAP changes, especially by those more likely to alter managers' information sets. Cheng et al. (2018) finds that firms affected by the accounting standard on acquired goodwill and other intangible assets (SFAS 142) provide more accurate management forecasts, consistent with managers acquiring better information while complying with a new accounting rule. Studies examining the adoption of lease accounting standards claim that firms' investment decisions are affected by the new rule due to the change in the manager's information set (e.g., Chen et al., 2022a). We contribute to this literature by showing an important channel through which the new accounting standard improves the adopting firms' information environment, namely the investment in information systems and human capital related to the new accounting standard.

2 Background, Literature, and Hypothesis

2.1 Institutional Background

The financial crisis of 2007–2009 sparked a debate about banks' financial reporting and their loan loss recognition in particular (Laux and Leuz, 2009, 2010; Barth and Landsman, 2010; Vyas, 2011; Beatty and Liao, 2011, 2014; Bushman and Williams, 2012, 2015; Huizinga and Laeven, 2012; Kothari and Lester, 2012; Acharya and Ryan, 2016; Wheeler, 2019, 2021; Bischof et al., 2021b; Kim, 2022). Regulators and others have blamed delays in loan loss provisioning under the existing accounting standard (FAS 5, ILM) for exacerbating the severity of economic downturns. They argue that the model's "probable" threshold for loss accrual and backward-looking nature induce banks to delay loss recognition in good times, creating an overhang of losses that carry forward to bad times. In response to this criticism, the FASB replaced the ILM of estimating credit losses with the CECL model in Accounting Standards Update (ASU) 2016-13 (ASC 326), effective January 1, 2020 (2023) for large public (small public and private) firms.[6,7]

The CECL approach mainly addresses the concerns above in two ways (Ryan, 2019). First, it eliminates the ILM's probable condition. Under the CECL model, a bank recognizes the amount of the expected credit losses on outstanding loans, even for those with a low probability of loss. Second, it substantially weakens the ILM's conditions regarding when losses are incurred and can be reasonably estimated. Banks are required to incorporate reasonable and supportable forecasts of future economic conditions into their estimates of expected credit losses and recognize credit losses on outstanding loans over their entire remaining lives at inception. In particular, the CECL approach explicitly "Requires an entity to consider forward-looking information rather than limiting consideration to current and past events, at the date of the statement of financial position" (FASB, 2016).

2.2 Related Research

Prior studies suggest the importance of banks' information production because it influences their operating and financial reporting choices. Qian et al. (2015) find that better information production by loan officers in Chinese banks improves the forecasting power of interest rates on future outcomes. Khan and Ozel (2016) find that banks' loan portfolios contain useful information about local economic conditions because banks collect detailed and proprietary information about the financial prospects of their customers. Lisowsky et al. (2017) show that banks collected less information from construction firms in the run-up to the financial crisis, which is closely associated with the lower lending standards before the housing

[6] ASU 2016–13 was initially set to take effect in January 2020 for all SEC filers, except for smaller reporting companies. However, due to the COVID-19 pandemic, the CARES Act provided firms with an option to delay CECL adoption until the earlier of (1) the first date of an eligible financial institution's fiscal year that begins after the date when the COVID-19 national emergency is terminated, or (2) January 1, 2022 (as amended by the Consolidated Appropriations Act). In addition, the FASB further pushed back the effective date of CECL implementation from January 2021 to January 2023 for smaller reporting companies, and from January 2022 to January 2023 for private and nonprofit entities.

[7] In August 2020, U.S. bank regulators issued the final rule that gave banks an option to mitigate estimated regulatory capital effects of CECL for two years, followed by a three-year transition period, therefore, allowing banks to have a transition period for up to five years.

crisis. Balakrishnan and Ertan (2021) find that banks' loan loss provisions become timelier after improved information sharing through public credit registries. Yang (2022) suggests that insufficient loan allowances during the financial crisis are attributable to low-quality information used for provisioning. These studies collectively highlight the critical role of banks' information production in their operating and reporting choices. Therefore, understanding the impact of CECL adoption on banks' information production process would help understand how and why CECL might affect banks' operating and reporting choices.

Several concurrent studies examine the impact of CECL adoption on banks' lending and risk-taking. For example, some studies examine the effects of CECL on lending procyclicality by employing either actual data under the CECL approach or simulated data under the ILM (e.g., Cohen and Edwards, 2017; Abad and Suarez, 2018; Covas and Nelson, 2018; Harris et al., 2018; Loudis and Ranish, 2019; Chae et al., 2020; Huber, 2021; Chen et al., 2022b; Lu and Nikolaev, 2022). These studies document mixed findings on the effects of CECL adoption on lending procyclicality, likely due to the different modeling assumptions for the simulated data or the limited data points under the CECL approach. Ballew et al. (2022) study banks' Paycheck Protection Program (PPP) participation. They find that the intensity of participation is associated with relatively greater changes in risk-taking outside of the PPP, and this effect is concentrated in banks that have not yet adopted CECL. Mahieux et al. (2022) study analytically the tradeoff between incurred loss (IL) and expected loss (EL) provisioning models and prudential regulation. They show that EL improves efficiency and provides more timely information when banks are insufficiently capitalized or when prudential regulatory interventions are likely to be effective. However, efficiency is impaired if banks are moderately capitalized and regulatory interventions are sufficiently costly.

Another related strand of research examines the effects of the adoption of IFRS 9 expected credit losses (ECL) model in 2018, which occurred two years earlier than CECL adoption. Lopez-Espinosa et al. (2021) document that provisions become more predictive of future bank risk after the ECL adoption. Kim et al. (2021) document that the adoption of

ECL improves loan loss recognition timeliness and thus mitigates the procyclicality of bank lending and risk-taking. Ertan (2021) shows that banks that adopted ECL reduce credit supply to small and medium-sized enterprises due to the difficulty in provisioning for more opaque borrowers. Bischof et al. (2021a) find that banks strategically adjust the internal ratings of their borrowers to minimize loan loss provisions. While these studies of IFRS 9 may provide some insights for the expected effects of CECL, their findings may not be replicated under CECL because ECL differs from CECL in several ways. The most notable difference is that under ECL, loans are classified into three stages based on credit quality, and losses are estimated for different horizons depending on the stage, whereas under CECL losses are estimated over the lifetime of the loan for all loans. In particular, under ECL, for loans classified as stage 1, which includes all new loans, credit losses are estimated over a one-year horizon, resulting in less provisions than under CECL (Lopez-Espinosa et al., 2021; Bischof et al., 2021a).

Three recent papers are closely related to our study. Beatty and Liao (2021) find analyst provision forecasts incrementally predict future non-performing loans (NPLs) and market returns, suggesting that the incurred loss provision does not incorporate all available future loss information, especially for banks facing greater ILM constraints. The CECL approach, therefore, could remove this constraint and allow banks to better incorporate their information into LLPs. Similarly, Wheeler (2021) estimates expected credit losses of loans using vintage analysis and finds that unrecognized expected credit losses under the ILM are negatively associated with bank stock prices. Lastly, Gee et al. (2022) find that newly recognized credit losses under CECL (i.e., the CECL day-1 impact from the adoption of the standard) improve the value relevance of credit loss allowances and their predictive ability for future credit losses.

These studies suggest that LLPs and allowances under the CECL model contain some decision-useful information. Prior studies do not differentiate whether CECL adoption just unlocks forward-looking information already available internally and make it public through financial reporting or it actually encourages banks to produce more forward-looking information about their customers and economic conditions. Our study differs from prior research because we examine whether the improved information contained in CECL allowances is driven by the better information production of the affected banks using loan-level confidential regulatory filings, and also provide potential channels through which this effect might arise.

2.3 Hypothesis Development

We hypothesize that because CECL adoption requires incorporating more forward-looking information and forecasts of economic conditions, banks would significantly update their information production process by collecting more information, investing more in information technology, and developing better forecasting models. Because information production is not directly observable, we instead test how CECL adoption affects banks' LLP recognition, LLP-related disclosure, and credit risk management. With better information production, we predict that (i) LLPs become timelier and more reflective of local economic conditions, (ii) LLP-related disclosures are more informative, and (iii) credit risk management benefits from better information.

While banks are expected to exert more effort in collecting, analyzing, organizing, and reporting information relevant to their loan portfolios under the CECL approach, such effects may not be salient and thus not improve the quality of reporting and operating decisions for several reasons. First, because forecasting the future is inherently challenging, the implementation of CECL is costly. Regulators and industry experts have commented that the cost of CECL implementation is high, especially for smaller banks with resource constraints (Stein, 2018; McWilliams, 2020). Second, banks often have inefficient or disjointed information systems due to mergers and acquisitions and geographic dispersion of branches. Thus, useful information on borrowers' credit profiles often resides with loan officers and does not end up being reported in an internal information system (Stein, 2002; Hertzberg et al., 2010). Finally, the CECL approach allows management more discretion and judgment in LLP than under the ILM (Walker, 2019; Kim, 2022). Thus, if banks had incentives to exploit the ILM opportunistically, they may exercise even more discretion under the CECL approach, resulting in minimal changes in improving banks' reporting and operating decisions. Hence, whether CECL adoption improves banks' information production processes and thus improves the quality of reporting and operating decisions is ultimately an empirical question. Given that the direction of our hypothesis is ambiguous, we state our null hypothesis as follows:

$\mathbf{H_0}$: CECL adoption does not increase banks' information production.

3 Data and Sample

We use quarterly bank-holding company data, including both public and private banks, with available variables on their FR Y-9C filings from 2017 Q1 to 2021 Q4. This period includes three years before large public banks adopted CECL and two years afterward. We require banks to have non-missing assets, deposits, changes in non-performing loans, lagged ratio of capital to assets, and earnings before loan loss provisions and taxes. We also require banks to have at least one-quarter of observations for both pre- and post-CECL adoption periods. After implementing these data requirements, we have 357 unique banks in the sample. To clearly identify the effects of CECL adoption, we exclude 20 foreign banks with headquarters outside of the U.S. because these banks were already subject to IFRS 9 starting from 2018.[8] We also exclude 53 banks with delayed adoption or adoption in different calendar quarters.[9]

[8]In loan-level analyses, we use some of these foreign banks as a control group and compare them to the U.S. CECL adopting banks.

[9]In our final sample, among public banks subject to CECL as of January 1, 2020, 42 banks elected to delay CECL adoption. Among them, 15 banks adopted CECL in 2020 Q4, 18 banks adopted CECL in 2021 Q1, and seven banks adopted CECL in 2022 Q1. In Table OA.3 of the online appendix, we examine the determinants of banks delaying CECL adoption as of 2019 Q4. Bank size is an important factor in predicting a bank's decision on delaying CECL adoption when the CARES Act was announced. In addition, to proxy

We determine whether banks adopt or delay CECL adoption by reading their 10-K filings and cross-checking with the information available in their FR Y-9C reports.[10] Banks that adopted CECL in January 2020 are defined as our treatment group, and banks that did not adopt CECL by December 2021 are our control group. The final sample consists of 5,488 bank-quarter observations representing 284 unique banks (150 CECL and 134 ILM banks).

For the loan-level analysis, we use FR Y-14Q regulatory filings that are collected quarterly as part of the Federal Reserve's Dodd-Frank Act Stress Tests (DFAST) and Comprehensive Capital Analysis and Review (CCAR) for bank holding companies (BHCs), savings and loan holding companies (SLHCs), and U.S. intermediate holding companies (IHCs) of foreign bank organizations with at least $50 billion ($100 billion starting from 2019) in total assets.[11] The banks that have submitted FR Y-14Q data since 2012 comprise over 85 percent of the total assets in the U.S. banking sector. The FR Y-14Q data include commercial and industrial (C&I) loans with a committed balance greater than or equal to $1 million (Caglio et al., 2022). We focus our analyses on schedule H, which contains detailed information on banks' loans to C&I borrowers. FR Y-14Q reporting banks that adopted CECL in 2020 are defined as our treatment group, and IHCs of foreign banks that adopted IFRS 9 in 2018 are our control group. The sample consists of 26 banks that adopted CECL and eight IHCs of foreign banks that adopted IFRS 9.

To proxy for the investment in information systems and human capital related to the adoption of the CECL methodology, we use job posting data provided by LinkUp. The data track the daily creation and deletion dates of online job postings by U.S. firms on their websites. The LinkUp data cover 127 out of 150 CECL banks in our sample.

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for banks' readiness for CECL adoption, we manually collected whether a bank provided any CECL impact estimation (either range or point estimates) in their 2019 10-K, an immediate quarter before the scheduled CECL adoption. We find that whether a bank provided a CECL impact estimate is another predictor. This finding suggests that small banks not fully prepared for CECL chose to delay its adoption when given the option.

[10] Items BHCKJJ20-BHCKJJ28 and BHCAJJ29 are reported only by banks that adopted CECL. We use this information to determine whether and when private banks adopt CECL. No private banks adopted CECL in January 2020, and hence none are included in our treatment group.

[11] Our findings using confidential FR Y-14Q data have been approved for public release.

Table 1 presents the descriptive statistics for our sample. Panel A provides the descriptive statistics of bank-level characteristics. The mean of LLPs is 0.081 percent of beginning-of-quarter total loans. The mean of LLPs for homogeneous (heterogeneous) loans, estimated as the change in allowance plus charge-offs, is 0.040 (0.044) percent of beginning-of-quarter total loans. We define LLPs for homogeneous or heterogeneous loans as missing if a bank is under the asset threshold to report allowance by loan type or does not hold certain types of loans. Columns (9) through (14) compare the mean values of these variables for CECL and ILM banks. The mean of LLPs is higher for CECL banks. Our control variables, *Size*, *EBLLP*, *Deposit*, and *CapRatio*, are significantly different between the two groups. We include bank fixed effects in all our regressions to control for unobserved differences, such as the business model differences between CECL and ILM banks. In addition, in Figure 1 and Figure 2, we check for parallel trends for LLPs and forward-looking statements by CECL and ILM banks before CECL adoption. As both figures show, we do not see any evidence that provisions and forward-looking words of CECL adopters differed from those of ILM banks prior to the implementation of CECL.

Panel B of Table 1 presents descriptive statistics of additional loan- or borrower-level characteristics for our loan-level analyses. Similar to our discussion above, we compare U.S. CECL banks to a comparison group of IHCs, foreign banks that have adopted IFRS 9 by 2018. As the table shows, on average, U.S. CECL banks have larger and less levered borrowers and are less likely to have loans with collateral or guarantees. They are also, on average, more likely to issue new loans and are less likely to lend to private borrowers. We check that both types of banks follow parallel trends for default rates and find that they are not significantly different prior to the implementation of CECL.[12]

[12] We report time-varying loan maturities in years. Term loans tend to have longer maturities on average. We include loan-type fixed effects in our empirical specification to account for some of the unobserved heterogeneity that might be due to loan type (loan types consist of different types of term loans including bridge and asset based loans as reported in FR Y-14Q, we exclude credit lines in our analyses). Our findings are also robust to using the natural logarithm of loan maturity instead.

4 Empirical Approach and Results

4.1 Information in Loan Loss Provisioning (LLP)

We begin our analyses by examining the properties of banks' LLPs, where we expect the most salient changes if banks produce higher quality information after CECL adoption. First, we examine whether the CECL approach increases the timeliness of banks' LLPs. The CECL approach requires banks to recognize expected credit losses by incorporating forward-looking information. If banks produce better information about their customers and economic conditions, they would quickly react to loan quality deterioration by recognizing timelier LLPs. Prior studies proxy the timeliness of LLPs as a positive relationship between current LLPs and changes in future non-performing loans (Nichols et al., 2009; Beatty and Liao, 2011; Bushman and Williams, 2015; Kim, 2022). Thus, if banks produce better information and that information is reflected in their LLPs, we expect the positive relationship between current LLPs and changes in future non-performing loans for the adopting banks to become stronger after CECL adoption.

Also, we expect the impact to be more substantial for heterogeneous loans (commercial real estate, construction, and commercial and industrial loans) than homogeneous loans (residential and consumer loans) for several reasons. Banks primarily evaluate credit losses for homogeneous loans at the portfolio level and typically record LLPs as expected loan charge-offs over the next 12 months. Depending on the type of homogeneous loans, 12 months can be similar to (e.g., credit card loans) or somewhat less than (e.g., auto loans and residential mortgages) the remaining lifetime of the loan (Ryan, 2019). Also, banks primarily evaluate credit losses for heterogeneous loans on a loan-by-loan basis, which requires more borrower-specific information to monitor and thus more effort to collect (Liu and Ryan, 2006; Bhat et al., 2021). Therefore, CECL adoption affects heterogeneous loans more than homogeneous loans.

We first examine the effects of CECL adoption on banks' LLPs with a simple graphical analysis. In Panel A of Figure 1, we plot the average proportion of LLPs to beginning total loans for CECL and ILM banks at the quarterly frequency from 2017 Q1 to 2021 Q4. Up to 2019 4Q, both CECL and ILM banks recorded similar proportions of LLPs to loans. Notably, both groups' LLPs show clear parallel trends until 2019 Q4. However, CECL banks increased LLPs significantly in 2020 Q1. This immediate jump is composed of the day-1 CECL adoption impact, estimated as of January 1, 2020, and additional upward adjustments during 2020 Q1, which reflect deteriorating economic conditions caused by the COVID-19 outbreak. However, CECL banks' LLPs significantly dropped from 2020 Q2 until 2021 Q2, during which immediate government responses to mitigate the economic impact of the COVID-19 pandemic came into effect. By contrast, ILM banks show a gradual increase in LLPs from 2020 Q1 until 2020 Q2 and then a gradual decrease, consistent with these banks provisioning for losses in a less timely manner than CECL banks.

In Panel B and Panel C, we plot the LLP trends for homogeneous and heterogeneous loans, respectively.[13] The general trends of LLP recognition for homogeneous loans are similar for both CECL and ILM banks except for the adoption quarter. By contrast, we see larger LLP recognition by CECL banks than ILM banks earlier in the COVID-19 pandemic period, followed by smaller LLP recognition by CECL banks afterward. These patterns are consistent with our prediction that the impact of CECL adoption on the timeliness of LLPs is likely larger for heterogeneous loans than homogeneous loans.

[13]Banks do not report LLPs by loan type in the FR Y-9C. We estimate LLPs by loan type as the change in allowance plus net charge-offs. As a result, we cannot separate the day-1 CECL adoption impact on LLPs by loan type from additional upward adjustments during 2020 Q1. Therefore, the day-1 CECL adoption impact is included in LLPs by loan type.

Next, we formally test this hypothesis using the following model:

$$
\begin{aligned}
LLP_{i,t} = {} & \beta_1 Treat_i \times Post_t \times \Delta NPL_{i,t_+} + \beta_2 Treat_i \times Post_t \times \Delta NPL_{i,t} \\
& + \beta_3 Treat_i \times Post_t \times \Delta NPL_{i,t_-} + \beta_4 Treat_i \times \Delta NPL_{i,t_+} + \beta_5 Treat_i \times \Delta NPL_{i,t} \\
& + \beta_6 Treat_i \times \Delta NPL_{i,t_-} + \beta_7 Post_t \times \Delta NPL_{i,t_+} \\
& + \beta_8 Post_t \times \Delta NPL_{i,t} + \beta_9 Post_t \times \Delta NPL_{i,t_-} + \beta_{10} Treat_i \times Post_t \\
& + \beta_{11} \Delta NPL_{i,t_+} + \beta_{12} \Delta NPL_{i,t} + \beta_{13} \Delta NPL_{i,t_-} + \beta_{14} X_{i,t} + \delta_t + \gamma_i + \epsilon_{i,t},
\end{aligned}
\tag{1}
$$

where i and t index bank and year-quarter, respectively. The dependent variable, $LLP_{i,t}$, is the bank's LLPs divided by lagged total loans. We also consider three variants of the dependent variable. LLP (w/ Day 1) adds the day-1 impact that bypasses the income statement.[14] LLP - Homog. and LLP - Hetero. are calculated as the quarterly change in allowance plus net charge offs for homogeneous (residential and consumer) and heterogeneous (construction, commercial real estate, and commercial and industrial) loans. Thus, these variables contain the day-1 CECL impact as well as other adjustments to allowance for loan losses, such as the expected credit losses on purchased credit deteriorated assets. The explanatory variable of interests is $Treat_i \times Post_t \times \Delta NPL_{i,t_+}$. $Treat_i$ is defined as an indicator that equals one if a bank adopted the CECL standard in 2020 Q1. $Post_t$ is an indicator variable that equals one for quarters after 2020. $\Delta NPL_{i,t_+}$ is the average future loan quality changes over the next two quarters, which is measured as the change in non-performing loans divided by lagged total loans. $\Delta NPL_{i,t}$ is the current loan quality changes. $\Delta NPL_{i,t_-}$ is the average past loan quality changes over the past two quarters. The calculation of ΔNPL varies with the choice of the dependent variable. We follow prior literature and include a number of control variables. In particular, $X_{i,t}$, includes $Size_{i,t}$, the natural logarithm of total assets, $EBLLP_{i,t}$, the earnings before the loan loss provision

[14] We obtain the day-1 impact of CECL adoption on loan loss provisions from item BHCKJJ28 in the FR Y-9C and, when it is missing, from 10-Q filings.

and taxes divided by lagged loans, $Deposit_{i,t}$, total deposits divided by total assets, and $CapRatio_{i,t-1}$, lagged ratio of capital to total assets. We include year-quarter fixed effects, δ_t, to control for economic conditions affecting all banks in each sample quarter and bank fixed effects, γ_i, to account for time-invariant bank characteristics.

Table 2 reports the estimation of Equation 1. In column (1), we examine the effects of CECL adoption on LLPs of total loans without the day-1 CECL impact (i.e., provisions recognized in the income statement in each quarter). The coefficient on $Treat_i \times Post_t \times \Delta NPL_{i,t_+}$ is significantly positive (0.320, p <0.05), suggesting that LLPs of CECL banks better reflect changes in future non-performing loans than that of ILM banks after CECL adoption. The finding is consistent with our hypothesis that CECL banks recognize expected credit losses in a timelier manner by incorporating forward-looking information. In column (2), we examine the effects of CECL adoption on LLPs of total loans by incorporating the day-1 CECL impact, and find consistent and even stronger results. The coefficient on $Treat_i \times Post_t \times \Delta NPL_{i,t_+}$ is significantly positive (0.512, p <0.01), suggesting that LLPs under the CECL approach, with or without the day-1 impact, contain useful information for current and future loan quality deterioration. In columns (3) and (4), we separately examine the effects of CECL adoption on LLPs of homogeneous and heterogeneous loans.[15] We find that the coefficient on $Treat_i \times Post_t \times \Delta NPL_{i,t_+}$ is statistically insignificant for homogeneous loans (-0.143, p >0.10) but is significantly positive for heterogeneous loans (0.521, p <0.01). These results indicate that the effects of CECL adoption on the timeliness of LLP recognition are mostly driven by heterogeneous loans, which is consistent with our prediction that the improvement in information production would be more substantial for loans requiring more borrower-specific information.[16]

[15] We have fewer observations for the tests using LLPs of homogeneous and heterogeneous loans because CECL banks with assets under $5 billion are only required to report allowances by loan type semiannually after 2020.

[16] In untabulated analysis, we also compare banks with low and high proportions of heterogeneous loans in their loan portfolios following other studies (e.g., Chen et al., 2022b). Consistent with our findings in Table 2, we find stronger CECL impacts for banks with high proportions of heterogeneous loans.

Next, we examine whether CECL banks' LLPs contain more information about local economic conditions in states where they operate. Khan and Ozel (2016) find that banks' loan portfolios contain useful information about local economic conditions because banks collect detailed and proprietary information about the financial prospects of their customers. If banks' LLPs reflect changes in local economic conditions better due to better information quality, we expect the negative relationship between current LLPs and changes in future local economic indicators to become stronger after CECL adoption. We proxy local economic conditions using the coincident index, a comprehensive measure of economic activity at the state level (Khan and Ozel, 2016).[17] We formally test this hypothesis using the following model:

$$
\begin{aligned}
LLP_{i,t} = & \beta_1 Treat_i \times Post_t \times \Delta CoIndex_{s,t_+} + \beta_2 Treat_i \times Post_t \times \Delta CoIndex_{s,t} \\
& + \beta_3 Treat_i \times Post_t \times \Delta CoIndex_{s,t_-} + \beta_4 Treat_i \times \Delta CoIndex_{s,t_+} \\
& + \beta_5 Treat_i \times \Delta CoIndex_{s,t} + \beta_6 Treat_i \times \Delta CoIndex_{s,t_-} \\
& + \beta_7 Post_t \times \Delta CoIndex_{s,t_+} + \beta_8 Post_t \times \Delta CoIndex_{s,t} + \beta_9 Post_t \times \Delta CoIndex_{s,t_-} \\
& + \beta_{10} Treat_i \times Post_t + \beta_{11} \Delta CoIndex_{s,t_+} + \beta_{12} \Delta CoIndex_{s,t} + \beta_{13} \Delta CoIndex_{s,t_-} \\
& + \beta_{14} X_{i,t} + \delta_t + \gamma_i + \epsilon_{i,t},
\end{aligned}
\tag{2}
$$

where i, t, and s index bank, year-quarter, and state, respectively. Same as before, the dependent variable is $LLP_{i,t}$ and its three variants. The explanatory variable of interests is $Treat_i \times Post_t \times \Delta CoIndex_{s,t_+}$. $CoIndex_{i,t_+}$ is the average future local economic condition changes over the next two quarters, which is measured as the weighted average of the coincident index based on banks' deposit shares in different states. $CoIndex_{s,t}$ is the current local economic condition change. $CoIndex_{i,t_-}$ is the average past local economic condition changes over the past two quarters. The same set of bank characteristics, as in Equation 1,

[17]The index is produced monthly by the Federal Reserve Bank of Philadelphia and calculated using models with four state-level inputs: nonfarm payroll employment, unemployment rate, average hours worked in manufacturing, and wage and salary disbursements deflated by the consumer price index.

is included as control variables. We also control for $\Delta NPL_{i,t}$, the changes in non-performing loans divided by lagged total loans. Finally, year-quarter fixed effects, δ_t, and bank fixed effects, γ_i, are included.

Table 3 reports the estimation of Equation 2. In column (1), we examine the effects of CECL adoption on LLPs of total loans without the day-1 CECL impact. The coefficient on $Post_t \times \Delta CoIndex_{s,t_+}$ is significantly positive (0.035, p <0.01), suggesting banks recognize more provisions when future local conditions are indeed better during the post period. This finding suggests that banks generally experienced difficulties incorporating future local conditions in their LLPs during the post period, which is likely driven by the increased uncertainty due to the pandemic. However, the coefficient on $Treat_i \times Post_t \times \Delta CoIndex_{s,t_+}$ is significantly negative (-0.035, p <0.01), suggesting the positive relationship between banks' LLPs and future local conditions during the post period is almost canceled out for CECL banks; presumably, they have better capability to forecast the economic conditions based on better information despite the increased uncertainty. In column (2), we examine the effects of CECL adoption on LLPs of total loans by incorporating the day-1 CECL impact, and find consistent results (-0.065, p <0.01). Again, these results suggest that both day-1 and subsequent LLPs of CECL banks contain useful information for current and future local economic conditions. We also further examine the effects of CECL adoption on LLPs of homogeneous and heterogeneous loans. In columns (3) and (4), we find that the coefficient on $Treat_i \times Post_t \times \Delta CoIndex_{s,t_+}$ is weakly significantly negative (-0.017, p <0.10) for homogeneous loans, and significantly negative (-0.029, p <0.01) for heterogeneous loans. These findings indicate that the effects of CECL adoption on the information production regarding local economic conditions are slightly stronger for heterogeneous loans.[18] However, the difference is not as salient as the results on the timeliness of LLPs. The less salient difference is likely because macroeconomic indicators, which are correlated with local economic con-

[18]In untabulated analysis, we also compare banks with low and high proportions of heterogeneous loans in their loan portfolios. We find stronger CECL impacts for banks with high proportions of heterogeneous loans.

ditions, are important inputs to determine LLPs for both homogeneous and heterogeneous loans.

4.2 Information in Disclosures

Next, we examine whether adopting banks provide better LLP-related disclosures after CECL adoption. Prior studies suggest that firms provide more frequent and more accurate disclosure when their internal information environments improve (Dorantes et al., 2013; Ittner and Michels, 2017; Cheng et al., 2018). Thus, if banks produce better information on their loan portfolios after CECL adoption, we expect CECL banks to provide more informative disclosures related to LLP in their financial reports. Specifically, we test whether CECL banks have longer, more forward-looking, and more quantitative information related to LLP in their 10-K filings.[19]

We use the number of sentences discussing LLPs to proxy an improvement in the quantity of LLP-related information.[20] However, an increase in the quantity of LLP-related disclosure does not necessarily suggest an improvement in the informativeness of such disclosure. For example, the added paragraphs could be boilerplate describing the new standard, such as how LLPs under CECL are calculated. To further examine whether LLP-related disclosure carries high-quality information, we search for sentences that contain a forward-looking word (e.g., Muslu et al., 2015; Bozanic et al., 2018) or a hard number (e.g., Dyer et al., 2017; Blankespoor, 2019) among those LLP-related sentences.[21] LLP sentences with forward-

[19]We focus on textual information in form 10-K rather than management guidance because the latter type of disclosure is rare in the banking industry.

[20]To identify LLP-related disclosures in banks' 10-Ks, we first normalize raw filings to address issues of punctuation, inflections, and extra white spaces. Then, we search for sentences that contain LLP-related words such as "provision," "allowance," "default," "charge off," "credit loss," and "loan loss." Next, we take the union of all sentences located within the $(-3, +3)$ window of the direct LLP-related sentences identified in the previous step to count the unique number of sentences.

[21]We start by pre-specifying a list of words deemed forward-looking. The list contains the stemmed forms of the following words: "anticipate," "believe," "estimate," "expect," "forecast," "predict," and "target." Next, we expand the list using word embedding. The natural language processing (NLP) technique identifies words that are likely to appear in the same contexts as the target words. We conduct word embedding using a large corpus of banks' 10-K filings. The expanded list additionally includes stemmed forms of

looking words are likely to be discussions about banks' evaluations of the macroeconomic environment and projections of indicators related to LLP calculation. LLP sentences with hard numbers provide quantitative information that is more specific and easier to notice, process, and compare.

Appendix C provides snapshots of JP Morgan Chase's LLP-related disclosures in its 10-K filings before and after CECL adoption. The first observation is that LLP-related discussions become longer after CECL adoption. Highlighted texts in the 2020 10-K are incremental LLP-related disclosures we intend to capture using the procedure outlined above.[22] Notably, these sentences either contain forward-looking words such as "assumption," "outlook," "forecast," and "scenario," or specific macroeconomic forecasts of unemployment rate and GDP growth (in numeric forms). This example illustrates the relevance and informativeness of LLP sentences that are forward-looking and quantitative.

Panel A of Figure 2 plots the number of sentences in banks' 10-K filings that are LLP-related from 2017 to 2021. Panel B and Panel C of Figure 2 further plot the number of LLP sentences that contain forward-looking words and hard numbers, respectively. As LLPs in Figure 1, both groups' LLP-related disclosures show clear parallel trends prior to CECL adoption. However, consistent with our prediction, the average quantity and quality of LLP-related disclosures increase for CECL banks compared to ILM banks after CECL adoption.

We formally test this hypothesis using the following model:

$$LLP\,Disc_{i,t} = \beta_1 Treat_i \times Post_t + \beta_2 X_{i,t} + \delta_t + \gamma_i + \epsilon_{i,t}, \tag{3}$$

where i and t index bank and year, respectively. The dependent variable, $LLP\,Disc_{i,t}$, takes three forms: *LLP Disc* is the natural logarithms of one plus the number of *unique* sentences

"aim," "assumption," "baseline," "future," "judgment," "outlook," "probably/probability," "scenario," and "(un)predictable."

[22]The table, which provides similar information is not highlighted because contents within HTML `<table>` tags are removed when processing 10-K documents.

falling within the $(-3, +3)$ window of any 10-K sentence in which there is an LLP sentence; *LLP Disc* - Fwd. is the natural logarithms of one plus the number of sentences containing forward-looking words among such LLP-related sentences; and *LLP Disc* - Quant. is the natural logarithms of one plus the number of sentences containing quantitative information (i.e., hard numbers) among such LLP-related sentences. The same set of bank characteristics, as in Equation 2 are included. Finally, year fixed effects, δ_t, and bank fixed effects, γ_i, are included.

Table 4 reports the estimation of Equation 3. In columns (1) through (3), we find that the coefficient on $Treat_i \times Post_t$ is significantly positive in all columns (0.124, p <0.01; 0.201, p <0.01; 0.085, p <0.01). The results suggest that managers at CECL banks provide longer, more forward-looking, and quantitative information than those at ILM banks after CECL adoption. These findings suggest LLP-related disclosures are improved for CECL banks both quantitatively and qualitatively, consistent with the prior studies showing the quantity and quality of disclosures improve when firms' internal information environments improve.

4.3 Do CECL Banks Produce Better Information?

In the previous section, we show that CECL banks' LLPs reflect future credit losses and local economic conditions better than those of ILM banks. One concern is that two different mechanisms could explain our findings. First, banks might already have all the information even before CECL adoption, and CECL adoption only affects banks' reporting behavior because it eliminates restrictions on recognizing LLPs under the ILM. Second, CECL adoption prompts banks to value the forward-looking estimation task more and thus exert more effort to produce forward-looking information about their customers and economic conditions. While these two mechanisms likely take place at the same time, we examine whether the second mechanism plausibly explains our findings by investigating loan-level default, observable in the confidential FR Y-14Q regulatory filings.

Prior studies suggest that monitoring borrowers is a major function of banks (Diamond, 1984; Rajan and Winton, 1995) and banks actively collect borrower information as part of their monitoring role (Gustafson et al., 2021). Research also suggests more information about borrowers leads to fewer defaults on banks' loans due to better screening and monitoring (Ertan et al., 2017; Lisowsky et al., 2017). If banks screen and monitor loans better by using more forward-looking information, we expect borrowers of CECL banks to exhibit fewer defaults following CECL. Furthermore, fewer defaults are unlikely to be driven by changes in reporting behavior but can be plausibly explained by banks producing better information. Examining loan-level default instead of bank-level NPLs or charge-offs allows us to control for borrower-specific credit risks and loan terms and explore cross-sectional differences across loan characteristics.

We examine the impact of CECL adoption on loan-level default using a difference-in-differences research design comparing large U.S. BHCs that adopted CECL in 2020 to foreign banks' U.S. IHCs that adopted ECL under IFRS 9 in 2018. The underlying assumption is that because these foreign banks have already adopted the ECL approach, an accounting standard similar to the CECL approach, earlier than the U.S. CECL banks, they can serve as a control group. To avoid any confounding effects of IFRS 9 adoption on foreign banks, we limit our sample to 2018–2021 for this analysis. We formally test this hypothesis using the following model:

$$Default_{i,j,k,t} = \beta_1 Treat_i \times Post_t + X_{i,t} + Y_{j,t} + Z_{k,t} + \delta_t + \gamma_i + \theta_j + \kappa_k + \epsilon_{i,j,k,t}, \tag{4}$$

where i, j, k and t index bank, borrower, loan, and quarter, respectively. The dependent variable is $Default_{i,j,k,t}$, an indicator that equals one if a loan defaults (i.e., 90 days past due) within four quarters of the reporting quarter.[23] The same set of bank characteristics, as

[23]Our results are robust to defining loan defaults as one if a loan is 30 days past due within four quarters of the reporting quarter.

in Equation 2, are included. We also control for borrower characteristics using the natural logarithm of total assets to control for borrower size, a ratio of total debt to total assets to control for leverage, and an indicator for whether the borrower is a private firm. We also control for loan characteristics including the probability of default (PD) assigned by the bank, loan maturity, and indicators for whether a loan includes collateral, is syndicated, is guaranteed, and is newly originated in a given year.[24] Finally, we include year-quarter, δ_t, bank, γ_i, borrower, θ_j, and loan-type fixed effects, κ_k.

Table 5 reports the estimation of Equation 4. In column (1), we find that the coefficient of $Treat_i \times Post_t$ is significantly negative (-0.003, p <0.01), consistent with CECL banks' borrowers experiencing lower default probabilities. To mitigate any concern that our results are driven by treatment banks having more PPP loans than our control banks, we exclude all loans with government guarantees, including PPP loans.[25] In column (2), we limit the sample to newly originated loans and find consistent results, mitigating any concern that loans originated prior to CECL adoption observed in post-adoption filings drive our results. In columns (3) and (4), we divide the sample into public and private borrowers, respectively. We find that the decrease in default is only significant for private borrowers (-0.003, p <0.01), consistent with a greater incremental impact of information production for more opaque borrowers. Lastly, in columns (5) and (6), we divide the sample into loans with low and high assigned probability of defaults (defined as below or above the median). We find that the decrease in default is stronger for loans with high PD (-0.003, p <0.01), consistent with a greater incremental impact of information production for riskier loans.

[24]We exclude credit lines as they are rolled over from year to year and can change terms and loans to individuals and municipalities.

[25]Our results are consistent if we instead compare within bank changes of pre- and post-CECL adoption periods for large U.S. BHCs that file FR Y-14Q.

4.4 Potential Mechanism

A natural follow-up question is through which channels CECL banks improve their information production. Recent studies suggest that financial institutions are increasingly investing in information technology and hiring experts to efficiently deal with regulatory monitoring, reporting, and compliance (Charoenwong et al., 2022). Relatedly, Bhat et al. (2019) suggest that credit risk modeling significantly improves banks' information about their credit losses. Arif et al. (2022) find that the quality of banks' human capital is associated with better loan monitoring and timelier loan loss provisioning. Thus, we conjecture that the investment in information systems and human capital related to CECL adoption is a plausible channel to improved information production. We proxy for information system and human capital investment using job-postings data following the approach in the literature (Hershbein and Kahn, 2018; Acemoglu et al., 2022). Specifically, we search terms, including "CECL," "Current Expected Credit Losses," "ASU 2016-13," "ASC 326," "Topic 326," and "Financial Instrument(s) Credit Loss(es)" in job descriptions, and label a job posting as a CECL-related job if it contains one of these terms.[26]

In Figure 3, we check the representativeness of LinkUp data by comparing them with the job opening data by the U.S. Bureau of Labor Statistics (BLS). The LinkUp data has fewer job postings than the BLS data because LinkUp only covers companies that list jobs on their own websites. However, the trends in the number of job postings are similar in both databases, assuring that the LinkUp data well reflects the labor market demand.

Figure 4 presents the number of CECL-related job postings. In Panel A of Figure 4, consistent with our prediction, CECL banks started posting CECL-related jobs a few years before 2020 (the adoption year), suggesting that these banks had prepared to comply with the CECL a while before the adoption. Notably, we observe a decrease in the number of

[26]Before searching for patterns, we normalize raw job postings to address issues of punctuation, inflections, and extra white spaces.

CECL job posting around the outbreak of COVID-19 in early 2020. However, the number of job postings surged from 2021, suggesting that adopting banks are increasingly investing in human capital with regard to the CECL approach over time.[27]

To understand the characteristics of CECL-related jobs, in Appendix B, we provide summary statistics of these job postings. In Panel A of Appendix B, we list the top 10 CECL job employers. Not surprisingly, large national banks, including Wells Fargo, Bank of America, and JPMorgan Chase, comprise a significant portion of CECL-related job postings, suggesting that larger banks have better resources for the investment in information technology and related-human capital.[28] Also, smaller banks have argued, and regulators have acknowledged that CECL adoption is more burdensome for smaller banks.[29]

In Panel B, we list the top 10 CECL job titles. Most CECL job titles contain words, including *Analytic*, *Credit Risk*, and *Quantitative*, which are highly associated with information production. Figure 5 presents word clouds of frequently used words in CECL job titles and descriptions. The word clouds also highlight words, including *analyst*, *credit*, *model*, and *risk*, related to information production, which provides assurance that CECL-related job postings is a suitable proxy for information systems and human capital investment.

In Panel C, we categorize these jobs based on the O*NET Standard Occupational Classification (SOC), which we obtain from LinkUp.[30] The SOC-based job titles and key tasks suggest that CECL jobs are mainly associated with three functions. First is managerial

[27] One potential concern is that observing few CECL-related job postings for ILM banks seems trivial, as these banks are not subject to CECL until 2023. To provide an alternative benchmark, in Panel B and Panel C of Figure 4, we define an informational job if a job shares any O*NET SOC codes with CECL-related jobs for ILM banks. Also, to mitigate bank size effects, we normalize job postings with the number of job postings in 2017 Q1. We find that the pattern of informational job postings by ILM banks is relatively stable compared to the increasing CECL-related job postings by CECL banks.

[28] We caveat that, among the top 4 commercial banks in the U.S., Citibank is not covered by the LinkUp database. However, we conjecture that Citibank has made extensive investments in CECL-related information systems and human capital.

[29] For that reason, smaller banks are also more likely to outsource to consultants or utilize models developed by other banks.

[30] The O*NET SOC is a federal standard used to classify occupations into approximately 1,000 categories. These occupations have associated data with occupational characteristics, including knowledge, skills, abilities, tasks, and general work activities. See (*link.*)

jobs related to managing customer relationships and thus likely to gather more information about them (e.g., Financial Managers). Second is quantitative jobs requiring skills related to analyzing and processing the data (e.g., Financial and Investment Analysts and Credit Analysts). The last is auditing jobs requiring skills related to financial reporting (e.g., Accountants and Auditors). Thus, CECL jobs generally relate to banks' information production process of collecting, analyzing, organizing, and reporting information.

To formally test the investment in information systems and human capital as a plausible mechanism, we conduct several cross-sectional tests by separating CECL banks that made large investments into CECL-related technology and human capital based on the median value of the cumulative number of CECL-related job postings from 2017 to a given year-quarter (i.e., Low- vs. High-CECL Jobs). We caveat that our proxy for investment in information systems and human capital cannot be fully distinguishable from a bank size effect. However, prior research suggests greater benefits of information-related investments for larger firms because technological investments have a large fixed component and information tends to have economies of scale (Wilson, 1975; Begenau et al., 2018; Charoenwong et al., 2022; Farboodi and Veldkamp, 2022).[31]

Table 6 reports the estimation of Equation 1 by comparing CECL banks with low- and high-CECL job postings to ILM banks. In columns (1) through (3), we examine the effects of CECL adoption for LLPs of total loans without the day-1 CECL impact for low-CECL job CECL banks, high-CECL job CECL banks, and high-CECL jobs and large CECL banks, respectively. We find that the coefficient on $Treat_i \times Post_t \times \Delta NPL_{i,t_+}$ is at least weakly significant for all three columns. Notably, the magnitude of the coefficient is larger for high-CECL job CECL banks and the largest for large CECL banks with high-CECL jobs. In columns (4) through (6), we examine the effects of CECL adoption for LLPs of total

[31]We also separate Low- vs. High-CECL jobs based on the number of CECL-related job postings scaled by the average number of bank employees or average assets, to remove the bank size effect, although this approach disproportionately penalizes larger banks. We find consistent but weaker differences between banks with Low- vs. High-CECL jobs if we use the scaled number of CECL-related job postings.

loans with the day-1 CECL impact and find a similar pattern. These findings are consistent with our prediction that the CECL impacts are larger for banks with a larger investment in information systems and human capital related to CECL adoption, and these effects are even more salient for larger banks (Wilson, 1975; Begenau et al., 2018; Charoenwong et al., 2022; Farboodi and Veldkamp, 2022).[32]

Table 7 reports the estimation of Equation 2 by comparing CECL banks with low- and high-CECL job postings to ILM banks. In columns (1) through (3), we examine the effects of CECL adoption on LLPs of total loans without the day-1 CECL impact. Similar to Table 6, we generally find that the magnitude of the coefficient on $Treat_i \times Post_t \times \Delta NPL_{i,t_+}$ is larger for high-CECL job and large CECL banks. In columns (4) through (6), we examine the effects of CECL adoption for LLPs of total loans with the day-1 CECL impact and find a similar pattern.[33]

Table 8 reports the estimation of Equation 3 by comparing CECL banks with low- and high-CECL job postings to ILM banks. Similar to previous tables, we generally find that the magnitude of the coefficient on $Treat_i \times Post_t$ increases with the number of CECL jobs and bank size. [34]

Lastly, we evaluate whether banks with higher CECL job postings see lower defaults. We repeat our analyses of Equation 4 by comparing Y-14Q reporting U.S. CECL banks with low- and high-CECL job postings to Y-14Q reporting foreign banks. Table 9 presents these results and shows that Y-14Q reporting U.S. CECL banks with higher CECL-related job postings experience significantly lower loan-level default (column 2). In column (3), we

[32]In untabulated analysis, we separately examine the effects of CECL adoption on LLPs of homogeneous and heterogeneous loans. We find a similar pattern of larger coefficients for high-CECL job banks and large CECL banks only for heterogeneous loans.

[33]Again, in untabulated analysis, we separately examine the effects of CECL adoption on LLPs of homogeneous and heterogeneous loans. We find a similar pattern of larger coefficients for high-CECL job CECL banks and large CECL banks for both homogeneous and heterogeneous loans.

[34]To reduce concern that the length of banks' 10-Ks or LLP-related disclosures is simply a function of their size, we take the log transformation of LLP-related disclosures. With bank fixed effects, we estimate the percentage change in the number of LLP-related sentences, which mitigates a mechanical relationship between the length of 10-K filings and bank size.

also find that this effect is more economically significant for the largest banks even in this sample of large U.S. BHCs.[35] These findings support our main results that investment into information systems and human capital is associated with lower future default risk.

Overall, our analyses using the job posting data suggest that the investment in information systems and human capital is a plausible mechanism for the impact of CECL adoption on banks' information production. These investments seem to be heterogeneous across banks and are more concentrated in larger banks, consistent with prior studies suggest that larger banks have better resources for the technology investment, and they enjoy greater benefits of those investments because information tends to have economies of scale (Wilson, 1975; Begenau et al., 2018; Charoenwong et al., 2022; Farboodi and Veldkamp, 2022).

4.5 Robustness Analyses

We conduct several robustness tests. First, we run the coarsened exact matching (CEM) analyses for the LLP analyses to mitigate concerns that bank-characteristic differences between CECL and ILM banks may affect our inferences. With CEM, we coarsen the data by dividing observations into five evenly spaced bins of control variables ($Size$, $EBLLP$, $Deposit$, and $CapRatio_{t-1}$) so that CECL and ILM banks have similar weighted histograms of these variables. Then, the weights are applied in a weighted least squares regression. In Table OA.1 of the online appendix, we find the regression coefficients and their statistical significance are similar to the analyses without matching. In addition, in untabulated analysis, we also repeat our analyses by limiting the sample to 2018–2021 to balance the pre- and post-CECL periods and find similar results. These additional tests suggest that our findings are robust to different model specifications and sample compositions.

Second, we address the concern that the difference in recognizing LLPs by CECL and ILM banks could be driven by the COVID-19 pandemic, which coincided with CECL adop-

[35] In percentage terms, the coefficient in column 3 is 0.323%, while the coefficient in column 2 is 0.289%.

tion. In particular, we examine the pattern of LLPs of banks that would have been subject to CECL and banks that would have been exempt from CECL around the financial crisis period (2005–2010). Mimicking the treatment and control groups described in ASU 2016-13, we define CECL banks as public banks except smaller reporting companies (SRCs) and ILM banks as smaller reporting companies and private banks as of 2007 Q4.[36] In Figure OA.1 of the online appendix, we plot the average proportion of LLPs to beginning total loans for hypothetical CECL and ILM banks at the quarterly frequency from 2005 to 2010. We see a gradual increase in LLPs for both banks during the crisis (2008–2009). Importantly, these patterns differ from the ones in Panel A of Figure 1 where we see an immediate jump in LLPs only for CECL banks in 2020 Q1, even before the pandemic effects are materialized. We believe this salient difference is consistent with CECL banks' LLPs in 2020 being driven by CECL adoption, although the pandemic could amplify its impacts. In addition, we replicate the timeliness of LLPs and reflection of local economic conditions in LLP analyses around the financial crisis period (i.e., $Post$ equals one for bank-quarters after 2008, and zero otherwise).[37] In Table OA.2 of the online appendix, we find that the coefficients on $Treat_i \times Post_t \times \Delta NPL_{i,t_+}$ and $Treat_i \times Post_t \times \Delta CoIndex_{s,t_+}$ are all statistically insignificant, suggesting that the timeliness of LLPs were not different for hypothetical CECL and ILM banks around the financial crisis, alleviating the concern that our findings are mainly driven by the pandemic effects.

5 Conclusion

We examine whether adopting the CECL model for loan loss provisioning improves banks' information production. We find that after CECL adoption, banks' LLP becomes timelier

[36]According to ASU 2016-13, public business entities, excluding SRCs as defined by the SEC, became subject to CECL for fiscal years beginning after December 15, 2019.

[37]Note that we could not run these analyses separately for homogeneous and heterogeneous loans because allowances by loan type used to estimate LLP by loan type are reported in FR Y-9C starting in 2013.

and better reflects local economic conditions. Consistent with banks producing better information under the CECL approach, we also find that banks provide better disclosures of LLPs in their 10-K filings and experience fewer loan-level defaults after CECL adoption. Notably, the effects of CECL on these outcomes increase with the number of CECL-related job postings, suggesting that investment in information systems and human capital is a plausible mechanism for improved information production.

Our study contributes to the literature on the consequences of CECL adoption, which fundamentally changes the way banks evaluate and provision for credit losses. Our findings suggest that accounting standards requiring the collection and analysis of forward-looking information can induce banks to produce and apply better information in their operating decisions. These findings also provide some important insights for banking regulation and supervision. In particular, our results that CECL leads banks to improve their evaluation and provisioning for credit losses can be used to explore loss rates in stress testing or inform procedures for loan-portfolio bank examinations. However, we also find that the CECL effects are more significant for larger banks, suggesting that the standard-driven benefits are likely more salient for large institutions with more resources to invest in technology and human capital.

We caveat that our findings are based on large public banks that adopted CECL in 2020 when the COVID-19 pandemic began. A short recessionary period right after CECL adoption provides an empirical setting to observe starkly different provisioning by CECL banks relative to ILM banks. However, we do not rule out that large banks may have responded differently from small banks to the recession without CECL adoption. Also, most CECL banks opted to delay the impact of CECL on regulatory capital, a regulatory relief granted in response to the pandemic. An open question for future research is whether the information production effects of CECL adoption that we document will also manifest for small public and private banks subject to CECL adoption in 2023.

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Appendices

A Variable Definitions

Variable	Definition
Treat	Equals one if the bank adopts CECL on January 1, 2020, and zero if the bank does not adopt CECL as of December 31, 2021. For Table 5 and Table 9, *Treat* equals one if the bank adopts CECL on January 1, 2020, and zero if the foreign bank adopts ECL under IFRS 9 in 2018.
Post	Equals one for bank-quarters Q1 2019 and afterwards, and zero for bank-quarters Q4 2018 and before.
LLP	Quarterly loan loss provisions (BHCK4230) divided by beginning total loans.
LLP (w/Day 1)	Quarterly loan loss provisions (BHCK4230) divided by beginning total loans but including day-1 impact for Q1 2020.
LLP - Homog.	Loan loss provisions for residential and consumer loans divided by beginning total loans, where provisions by loan type is estimated as ending allowance minus beginning allowance plus quarterly net charge-offs by loan type.
LLP - Hetero.	Loan loss provisions for construction, commercial real estate, and commercial/industrial loans divided by beginning total loans, where provisions by loan type is estimated as ending allowance minus beginning allowance plus quarterly net charge-offs by loan type.
ΔNPL	Ending non-performing loans (NPL) (BHCK5526 before 2018 and BHCK1403 after 2018) minus beginning NPL divided by beginning total loans.
ΔNPL - Homog.	Change in non-performing loans for residential and consumer loans divided by beginning total loans.
ΔNPL - Hetero.	Change in non-performing loans for construction, commercial real estate, and commercial/industrial loans divided by beginning total loans.
$\Delta CoIndex$	Quarterly change in the weighted average of state-level coincident index based on banks' deposit shares in different states.
Size	Natural logarithm of the banks' beginning total assets (BHCK2170) in millions. Banks with an above-median total assets in a given year-quarter are considered large banks.
EBLLP	Earnings before loan loss provision and taxes (BHCK4301+BHCK4230) divided by beginning total loans (BHCKB528).
Deposit	Total deposits (BHDM6631+BHDM6636+BHFN6631+BHFN6636) divided by total assets (BHCK2170).
CapRatio	Total equity capital (BHCKG105) divided by total assets (BHCK2170).

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Variable	**Definition**
LLP Disc.	The natural logarithm of one plus the number of LLP-related sentences in the bank's 10-K.
LLP Disc. - Fwd.	The natural logarithm of one plus the number of LLP-related sentences that are forward-looking in the bank's 10-K.
LLP Disc. - Quant.	The natural logarithm of one plus the number of LLP related sentences with quantitative information in the bank's 10-K.
$Size^B$	Natural logarithm of the borrowers' total assets as reported in the FR Y-14Q.
Leverage	The ratio of the borrowers' total debt relative to total assets as reported in the FR Y-14Q and zero otherwise.
Private	Equals one if a borrower is privately-held as reported in the FR Y-14Q and zero otherwise.
Default	Equals one if a loan defaults (i.e., 90 days past due) during the four quarters after the reporting quarter and zero otherwise.
PD	Probability of default for a given loan as reported in the FR Y-14Q.
Maturity	Loan maturity in years as reported in the FR Y-14Q.
Collateral	Equals one if a loan is collateralized as reported in the FR Y-14Q and zero otherwise.
Guaranteed	Equals one if a loan is guaranteed as reported in the FR Y-14Q and zero otherwise.
Syndicated	Equals one if a loan is part of a syndicate as reported in the FR Y-14Q and zero otherwise.
New	Equals one if a loan is originated in the quarter of reporting as reported in the FR Y-14Q and zero otherwise.
CECL Jobs - Low	CECL banks with a below-median number of cumulative CECL-related job postings from 2017 up to a given year-quarter.
CECL Jobs - High	CECL banks with an above-median number of cumulative CECL-related job postings from 2017 up to a given year-quarter.

B Summary Statistics of CECL-related Job Postings

This appendix provides summary statistics of the CECL-related job postings on LinkUp. Panel A lists the top 10 banks with the most CECL-related job postings in 2017–2021. Panel B lists the top 10 job titles that we define as CECL-related. Panel C lists the most common SOC job classifications for CECL-related job postings and their job descriptions according to O*NET.

Panel A: Top 10 CECL Job Employers

Bank	No. CECL Jobs	% of All CECL Jobs	Cum. % of All CECL Jobs
Wells Fargo	1012	24.2%	24.2%
Bank of America	595	14.2%	38.5%
JPMorgan Chase	580	13.9%	52.4%
PNC Financial	381	9.1%	61.5%
SVB Financial Group	154	3.7%	65.2%
Keybank	99	2.4%	67.5%
American Express	95	2.3%	69.8%
Discover Financial Services	74	1.8%	71.6%
TD Bank	74	1.8%	73.4%
Morgan Stanley	69	1.7%	75.0%

Panel B: Top 10 CECL Job Titles

Job Title	No. CECL Jobs	% of All CECL Jobs	Cum. % of All CECL Jobs
Credit Risk Analytics Consultant	168	4.0%	4.0%
Quantitative Finance Analyst	166	4.0%	8.0%
Quantitative Analytics Specialist	153	3.7%	11.7%
Analytic Consultant	101	2.4%	14.1%
Credit Risk Analytics Associate	46	1.1%	15.2%
Credit Risk Analytics Officer	44	1.1%	16.2%
Quantitative Analytics Consultant	42	1.0%	17.2%
Risk Analysis Specialist	42	1.0%	18.2%
Credit SEC Reporting Analyst	41	1.0%	19.2%
Quantitative Financial Analyst	38	0.9%	20.1%

Panel C: SOC Categories of CECL-related Jobs

SOC	Title	% of CECL Jobs	Top 5 Responsibilities
13-2051.00	Financial Analysts & Investment Analysts	32.8%	-Advise clients on aspects of capitalization, such as amounts, sources, or timing. -Analyze financial or operational performance of companies facing financial difficulties to identify or recommend remedies. -Assess companies as investments for clients by examining company facilities. -Collaborate on projects with other professionals, such as lawyers, accountants, or public relations experts. -Collaborate with investment bankers to attract new corporate clients.
11-3031.02	Financial Managers	23.6%	-Establish and maintain relationships with individual or business customers or provide assistance with problems these customers may encounter. -Plan, direct, or coordinate the activities of workers in branches, offices, or departments of establishments, such as branch banks, brokerage firms, risk and insurance departments, or credit departments. -Recruit staff members. -Prepare operational or risk reports for management analysis. -Evaluate data pertaining to costs to plan budgets.
13-1111.00	Management Analysts	17.0%	-Document findings of study and prepare recommendations for implementation of new systems, procedures, or organizational changes. -Interview personnel and conduct on-site observation to ascertain unit functions, work performed, and methods, equipment, and personnel used. -Analyze data and other information gathered to develop solutions or alternative methods of proceeding. -Plan study of work problems, such as organizational change, communications, information flow, integrated production methods, inventory control, or cost analysis. -Confer with personnel concerned to ensure successful functioning of newly implemented systems or procedures.

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SOC	Title	% of CECL Jobs	Top 5 Responsibilities
13-2041.00	Credit Analysts	10.1%	-Analyze credit data and financial statements to determine the degree of risk involved in extending credit or lending money. -Complete loan applications, including credit analyses and summaries of loan requests, and submit to loan committees for approval. -Generate financial ratios, using computer programs to evaluate customers' financial status. -Prepare reports that include the degree of risk involved in extending credit. -Analyze financial data, such as income growth, quality of management, and market share to determine expected profitability of loans.
13-1161.00	Market Research & Marketing Specialists	3.5%	-Prepare reports of findings, illustrating data graphically and translating complex findings into written text. -Collect and analyze data on customer demographics, preferences, needs, and buying habits to identify potential markets and factors affecting product demand. -Conduct research on consumer opinions and marketing strategies, collaborating with marketing professionals, statisticians, pollsters, and other professionals. -Measure and assess customer and employee satisfaction. -Devise and evaluate methods and procedures for collecting data, such as surveys, opinion polls, or questionnaires, or arrange to obtain existing data.
13-2011.01	Accountants & Auditors	3.4%	-Prepare detailed reports on audit findings. -Report to management about asset utilization and audit results, and recommend changes in operations and financial activities. -Collect and analyze data to detect deficient controls, duplicated effort, extravagance, fraud, or non-compliance with laws, regulations, and management policies. -Inspect account books and accounting systems for efficiency, effectiveness, and use of accepted accounting procedures to record transactions. -Supervise auditing of establishments, and determine scope of investigation required.

C Examples of Pre- and Post-CECL LLP Disclosures

This appendix illustrates differences in LLP-related disclosures between JPMorgan Chase's 2019 and 2020 10-Ks. We select the first page in each year's 10-K that is specifically dedicated to discussions of LLP. The same page repeats in financial statement footnotes. Highlighted texts reflect added LLP disclosures that are forward-looking and/or quantitative. Note that the table is not captured by the algorithm described in subsection 4.2, since all tables are dropped when processing 10-K filings. Importantly, the incremental disclosure in 2020's 10-K persists into 2021.

JP Morgan Chase 2019 10-K

Management's discussion and analysis

ALLOWANCE FOR CREDIT LOSSES

The Firm's allowance for credit losses covers the retained consumer and wholesale loan portfolios, as well as the Firm's wholesale and certain consumer lending-related commitments.

Refer to Critical Accounting Estimates Used by the Firm on pages 136-138 and Note 13 for further information on the components of the allowance for credit losses and related management judgments.

At least quarterly, the allowance for credit losses is reviewed by the CRO, the CFO and the Controller of the Firm. As of December 31, 2019, JPMorgan Chase deemed the allowance for credit losses to be appropriate and sufficient to absorb probable credit losses inherent in the portfolio.

The allowance for credit losses decreased compared with December 31, 2018 driven by:

- an $800 million reduction in the CCB allowance for loan losses, which included $650 million in the PCI residential real estate portfolio, reflecting continued improvement in home prices and delinquencies; $100 million in the non credit-impaired residential real estate portfolio; and $50 million in the business banking portfolio; as well as
- a $151 million reduction for write-offs of PCI loans,

predominantly offset by

- a $500 million addition to the allowance for loan losses in the credit card portfolio reflecting loan growth and higher loss rates as newer vintages season and become a larger part of the portfolio, and
- a $251 million addition in the wholesale allowance for credit losses driven by select client downgrades.

Refer to Consumer Credit Portfolio on pages 103-107, Wholesale Credit Portfolio on pages 108-115 and Note 12 for additional information on the consumer and wholesale credit portfolios.

JP Morgan Chase 2020 10-K

Management's discussion and analysis

ALLOWANCE FOR CREDIT LOSSES

Effective January 1, 2020, the Firm adopted the CECL accounting guidance. The adoption of this guidance established a single allowance framework for all financial assets measured at amortized cost and certain off-balance sheet credit exposures. This framework requires that management's estimate reflects credit losses over the instrument's remaining expected life and considers expected future changes in macroeconomic conditions. Refer to Note 1 for further information.

The Firm's allowance for credit losses comprises:

- the allowance for loan losses, which covers the Firm's retained loan portfolios (scored and risk-rated) and is presented separately on the Consolidated balance sheets,
- the allowance for lending-related commitments, which is presented on the Consolidated balance sheets in accounts payable and other liabilities, and
- the allowance for credit losses on investment securities, which covers the Firm's HTM and AFS securities and is recognized within Investment Securities on the Consolidated balance sheets.

The allowance for credit losses increased compared with December 31, 2019, primarily reflecting the deterioration and uncertainty in the macroeconomic environment, in particular in the first half of 2020, as a result of the impact of the COVID-19 pandemic, consisting of:

- a net $7.4 billion addition in consumer, predominantly in the credit card portfolio, and
- a net $4.7 billion addition in wholesale, across the LOBs, impacting multiple industries.

The adoption of CECL on January 1, 2020, resulted in a $4.3 billion addition to the allowance for credit losses.

Discussion of changes in the allowance during 2020

The increase in the allowance for loan losses and lending-related commitments was primarily driven by an increase in the provision for credit losses, reflecting the deterioration in and uncertainty around the future macroeconomic environment as a result of the impact of the COVID-19 pandemic.

As of December 31, 2020, the Firm's central case reflected U.S. unemployment rates of approximately 7% through the second quarter of 2021 and remaining above 5% until the second half of 2022. This compared with relatively low levels of unemployment of approximately 4% throughout 2020 and 2021 in the Firm's January 1, 2020 central case.

Further, while the Firm's January 1, 2020 central case U.S. GDP forecast reflected a 1.7% expansion in 2020, actual U.S. GDP contracted approximately 2.5% in 2020. As of December 31, 2020, the Firm's central case assumptions reflect a return to pre-pandemic GDP levels in the fourth quarter of 2021.

Due to elevated uncertainty in the near term outlook, driven by the potential for increased infection rates and related lock downs resulting from the pandemic, as well as the prospect that government and other consumer relief measures set to expire may not be extended, the Firm has placed significant weighting on its adverse scenarios. These scenarios incorporate more punitive macroeconomic factors than the central case assumptions, resulting in weighted average U.S. unemployment rates remaining elevated throughout 2021 and 2022, ending the fourth quarter of 2022 at approximately 6%, and in U.S. GDP ending 2022 approximately 0.9% higher than fourth quarter 2019 actual pre-pandemic levels.

The Firm's central case assumptions reflected U.S. unemployment rates and U.S. real GDP as follows:

	Assumptions at January 1, 2020		
	2Q20	4Q20[b]	2Q21
U.S. unemployment rate[a]	3.7 %	3.8 %	4.0 %
Cumulative change in U.S. real GDP from 12/31/2019	0.9 %	1.7 %	2.4 %
	Assumptions at December 31, 2020		
	2Q21	4Q21	2Q22
U.S. unemployment rate[a]	6.8 %	5.7 %	5.1 %
Cumulative change in U.S. real GDP from 12/31/2019	(1.9)%	0.6 %	2.0 %

(a) Reflects quarterly average of forecasted U.S. unemployment rate.
(b) 4Q20 actual U.S. unemployment rate (quarterly average) was 6.8%. 4Q20 actual cumulative change in U.S. real GDP from 4Q19 was (2.5%).

Subsequent changes to this forecast and related estimates will be reflected in the provision for credit losses in future periods. Refer to Note 13 and Note 10 for a description of the policies, methodologies and judgments used to determine the Firm's allowances for credit losses on loans, lending-related commitments, and investment securities.

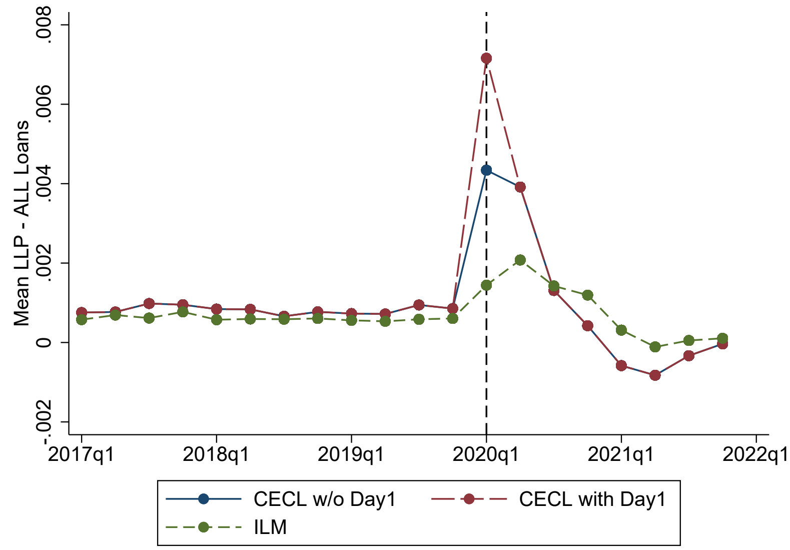
Refer to Critical Accounting Estimates Used by the Firm on pages 152-155 for further information on the allowance for credit losses and related management judgments.

Refer to Consumer Credit Portfolio on pages 114-120, Wholesale Credit Portfolio on pages 121-131 and Note 12 for additional information on the consumer and wholesale credit portfolios.

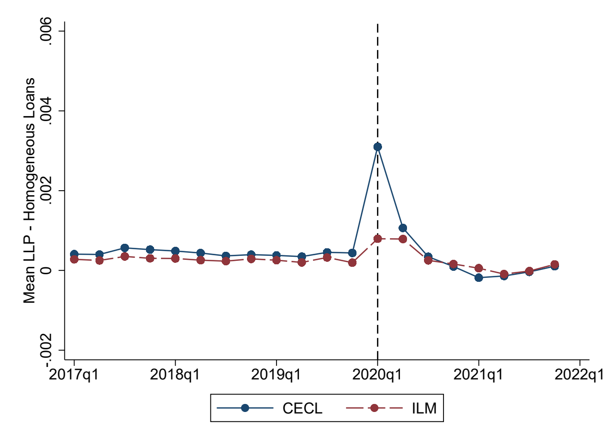
Figure 1: Loan Loss Provisioning

This figure plots the average loan loss provisioning to beginning total loans of banks that adopted CECL on January 1, 2020 (CECL) and banks not subject to CECL adoption (ILM). Panel A reports LLPs for total loans. For CECL adopting banks, we additionally plot the LLPs with the day-1 impact for Q1 2020, which bypasses the income statement. Panel B and Panel C report LLPs for homogeneous and heterogeneous loans, respectively. For homogeneous and heterogeneous loans, LLPs are estimated as the change in the allowance plus net charge-offs for each loan type.

Panel A: LLP - All Loans



Panel B: LLP - Homog. Loans



Panel C: LLP - Hetero. Loans

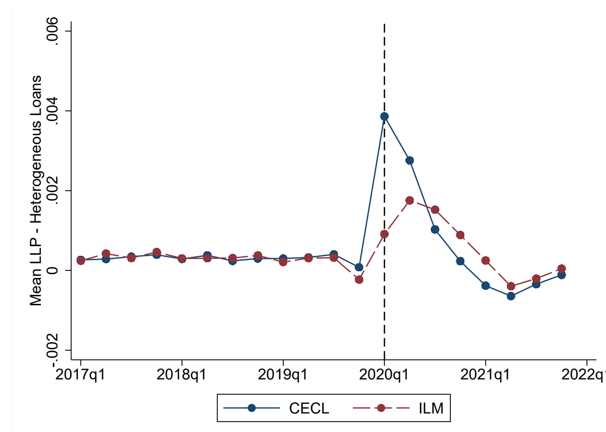
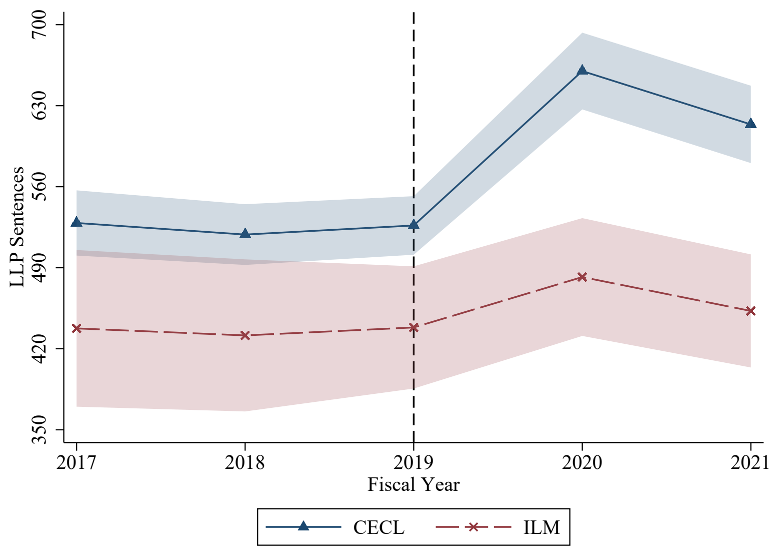


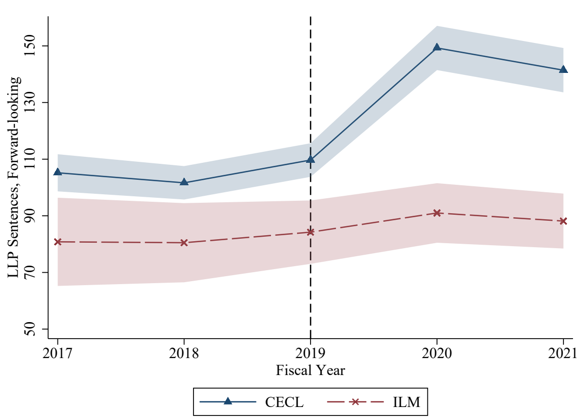
Figure 2: LLP-related Disclosure

This figure plots the number of LLP-related sentences in 10-Ks by banks that adopted CECL on January 1, 2020 (CECL) and banks not subject to CECL adoption (ILM). Panel A reports the number of *unique* sentences falling within the (-3,+3) window of any 10-K sentence in which there is an LLP sentence. Panel B and Panel C reports the number of sentences containing forward-looking words and quantitative information (i.e., hard numbers) among such LLP-related sentences, respectively. The shaded areas represents 95% confidence intervals.

Panel A: LLP Disc. - All Sentences



Panel B: LLP Disc. - Fwd. Sentences



Panel C: LLP Disc. - Quant. Sentences

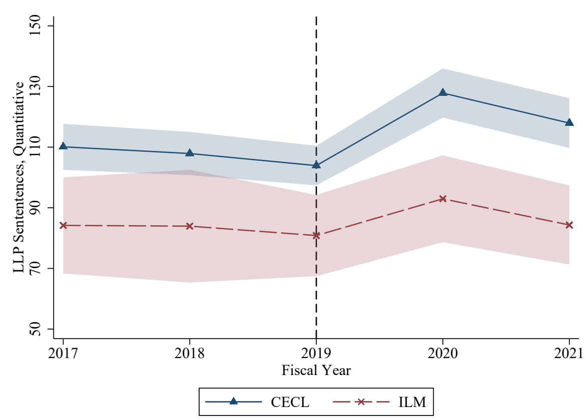
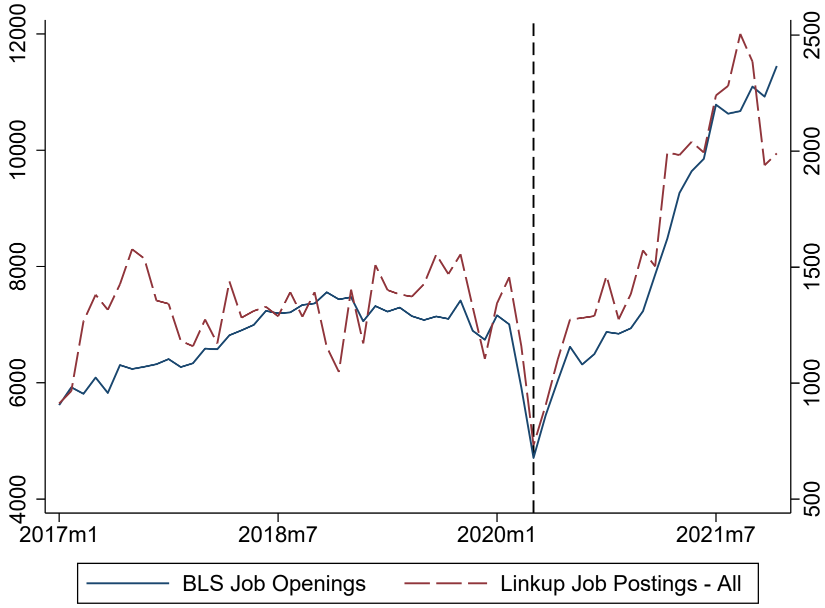


Figure 3: Time Trends of Job Postings

This figure plots the number of job openings reported by the Bureau of Labor Statistics (left axis in thousands) and the number of job postings in LinkUp (right axis in thousands). Panel A plots the LinkUp numbers for all industries and Panel B plots the LinkUp numbers for banks only.

Panel A: BLS Openings vs. LinkUp Postings – All



Panel B: BLS Openings vs. LinkUp Postings – Banks

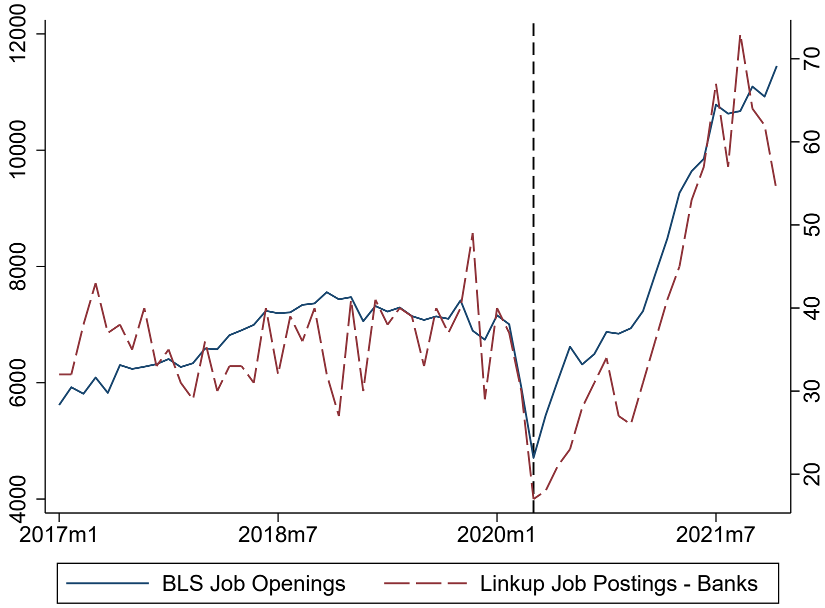
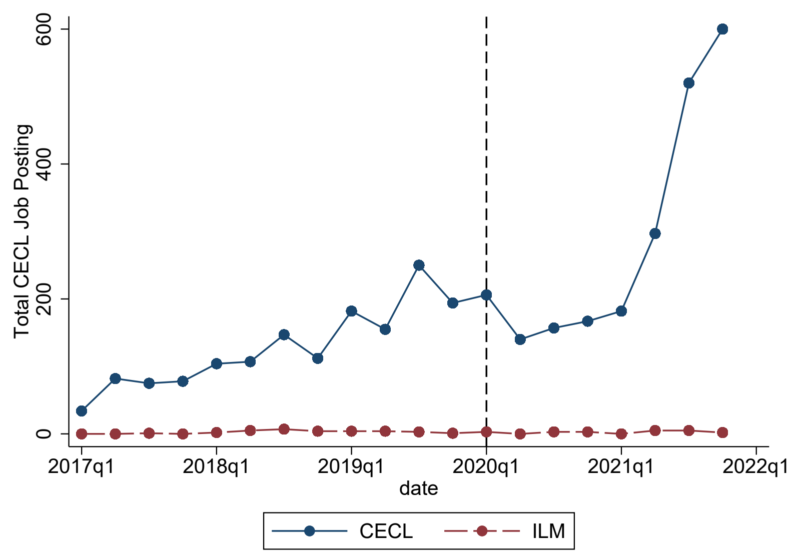


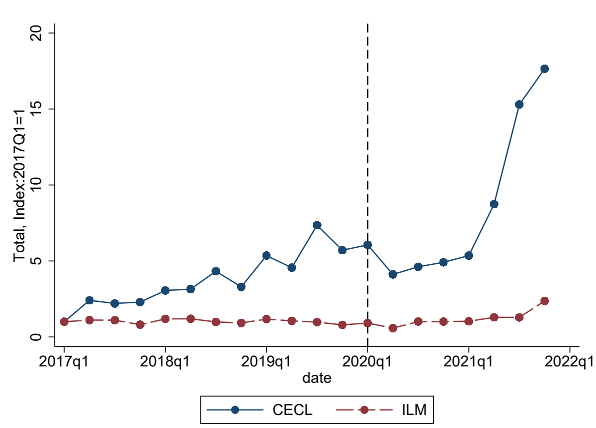
Figure 4: Number of CECL-related Job Postings for CECL vs. ILM Banks

This figure plots CECL-related and informational job postings on LinkUp by banks that adopted CECL on January 1, 2020 (CECL) and banks not subject to CECL adoption (ILM). A CECL-related job is defined if job descriptions contain one of terms "CECL," "Current Expected Credit Losses," "ASU 2016-13," "ASC 326," "Topic 326," and "Financial Instrument(s) Credit Loss(es)." An informational job is defined if a job shares any O*NET SOC codes with CECL-related jobs. Panel A plots the total number of CECL-related job postings by CECL and ILM banks, Panel B plots the total number of CECL-related (informational) job postings by CECL (ILM) banks, and Panel C plots the average number of CECL-related (informational) job postings by CECL (ILM) banks. Panel B and Panel C are indexed to 2017 Q1.

Panel A: Total CECL Job Postings



Panel B: Total CECL (Informational) Job Postings, Index: 2017Q1=1



Panel C: Mean CECL (Informational) Job Postings, Index: 2017Q1=1

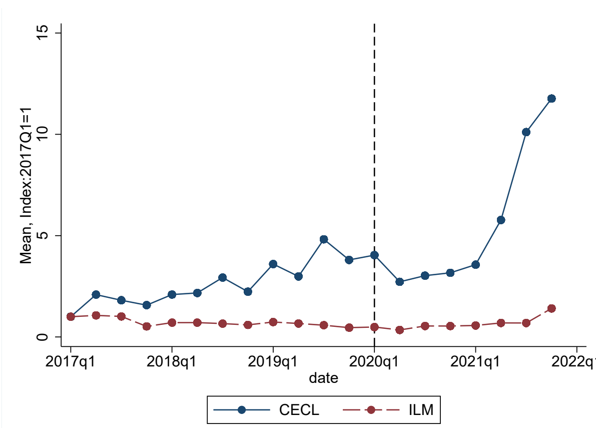
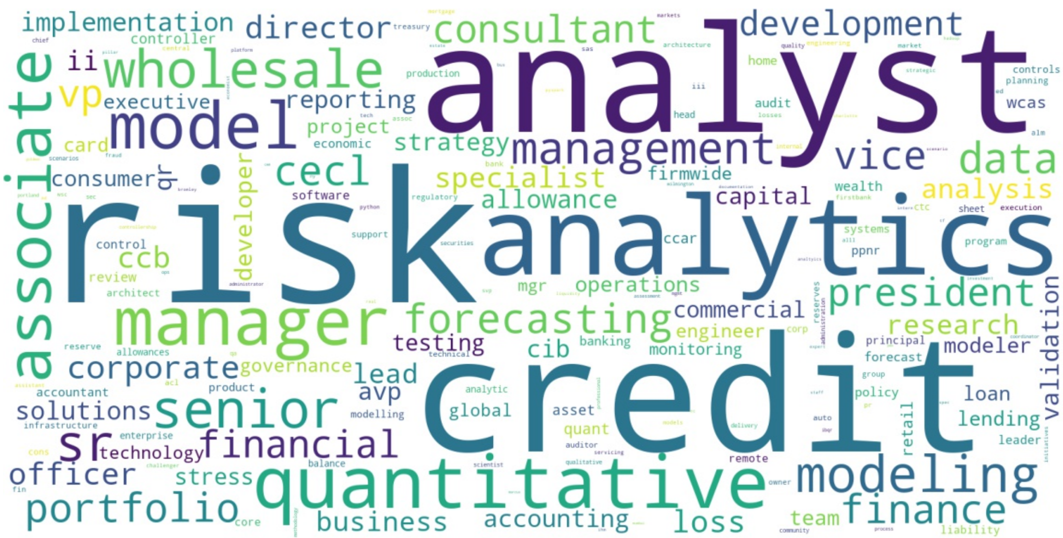


Figure 5: Frequently Used Words in CECL-related Job Postings

This figure plots word clouds for the most frequently used words in CECL-related job postings. The word clouds are generated using bag-of-words (BOW) document vectors. Panel A displays the words used in the job titles. Panel B displays the words used in the job descriptions. Larger font sizes indicate higher frequency.

Panel A: Word Cloud: Job Titles



Panel B: Word Cloud: Job Descriptions

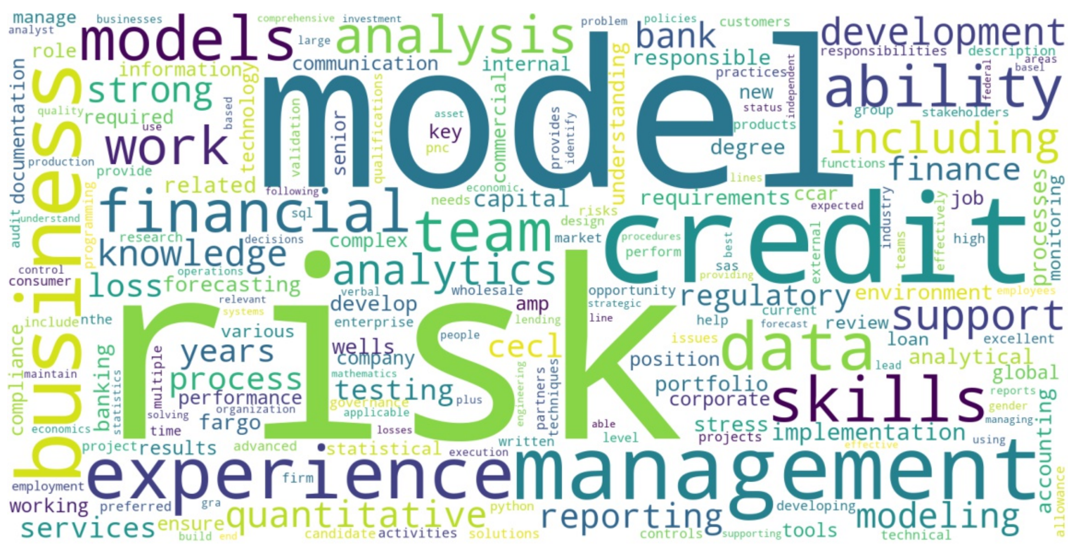


Table 1: Descriptive Statistics

This table reports the descriptive statistics. Variables expressing LLP and ΔNPL are in percentages. Panel A presents summary statistics of bank-level characteristics. Panel B presents summary statistics of additional loan- or borrower-level characteristics for our loan-level analyses. Columns (1) to (8) provide descriptive statistics for the full sample. Columns (9) to (14) show the mean differences for the samples of CECL and control banks (ILM banks in Panel A and IHCs in Panel B). All variables are defined in Appendix A. *, **, and *** indicate statistical significance of the mean differences at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Full Sample								CECL Banks		Crtl. Banks		Two-sample t-test	
	N	Mean	Std. Dev.	10th	25th	Median	75th	90th	N	Mean	N	Mean	Diff.	p-value
Panel A. Bank-level Chars.														
LLP	5,488	0.081	0.196	-0.026	0.005	0.038	0.086	0.215	2,941	0.091	2,547	0.069	0.021***	<0.001
LLP (w/Day 1)	5,488	0.089	0.232	-0.026	0.005	0.037	0.086	0.223	2,941	0.105	2,547	0.070	0.035***	<0.001
LLP - Homog.	4,544	0.040	0.167	-0.022	-0.003	0.007	0.029	0.083	2,886	0.048	1,658	0.027	0.021***	<0.001
LLP - Hetero.	4,539	0.044	0.137	-0.042	-0.002	0.020	0.055	0.142	2,888	0.050	1,651	0.034	0.016***	<0.001
ΔNPL	5,488	0.004	0.197	-0.147	-0.058	-0.006	0.045	0.165	2,941	0.004	2,547	0.004	-0.000	0.975
Δ*CoIndex*	5,068	0.007	0.044	0.001	0.005	0.009	0.014	0.027	2,852	0.007	2,216	0.007	0.000	0.909
Size	5,488	9.084	1.579	7.328	8.057	8.757	9.845	11.125	2,941	9.930	2,547	8.106	1.824***	<0.001
EBLLP	5,488	0.008	0.012	0.004	0.005	0.006	0.008	0.012	2,941	0.009	2,547	0.008	0.001***	<0.001
Deposit	5,488	0.772	0.126	0.664	0.749	0.801	0.844	0.869	2,941	0.759	2,547	0.788	-0.029***	<0.001
CapRatio	5,488	0.116	0.039	0.082	0.095	0.110	0.128	0.150	2,941	0.120	2,547	0.112	0.008***	<0.001
LLP Disc.	851	6.233	0.479	5.897	6.125	6.297	6.471	6.644	728	6.266	123	6.037	0.229***	<0.001
LLP Disc. - Fwd.	851	4.654	0.551	4.220	4.489	4.718	4.956	5.170	728	4.701	123	4.373	0.329***	<0.001
LLP Disc. - Quant.	851	4.582	0.578	4.094	4.407	4.673	4.913	5.112	728	4.624	123	4.334	0.290***	<0.001
Panel B. Borrower- or Loan-level Chars.														
$Size^B$	716,558	18.547	3.011	15.037	16.398	18.053	20.510	22.771	657,970	18.579	58,588	18.188	0.391***	<0.001
Leverage	716,558	0.397	0.253	0.093	0.208	0.361	0.549	0.744	657,970	0.394	58,588	0.438	-0.044***	<0.001
Private	716,558	0.838	0.368	0	1	1	1	1	657,970	0.836	58,588	0.863	-0.027***	<0.001
Default	716,558	0.003	0.055	0	0	0	0	0	657,970	0.003	58,588	0.004	-0.001***	<0.001
PD	716,558	0.020	0.042	0.001	0.004	0.009	0.019	0.038	657,970	0.020	58,588	0.023	-0.002***	<0.001
Maturity	716,491	48.823	590.953	0.885	2.252	3.921	6.027	9.348	657,967	47.293	58,524	66.024	-18.732***	<0.001
Collateral	716,558	0.910	0.287	1	1	1	1	1	657,970	0.909	58,588	0.921	-0.012***	<0.001
Guaranteed	716,558	0.496	0.500	0	0	0	1	1	657,970	0.486	58,588	0.613	-0.128***	<0.001
Syndicated	716,558	0.188	0.391	0	0	0	0	1	657,970	0.189	58,588	0.179	0.009***	<0.001
New	716,558	0.068	0.252	0	0	0	0	0	657,970	0.070	58,588	0.045	0.025***	<0.001

Table 2: Timeliness of Loan Loss Provisioning

This table reports the results of estimating the timeliness of LLPs using Equation 1. The dependent variables in columns (1)–(4) are LLPs for all loans, LLPs with day-1 impact for all loans, LLPs for homogeneous loans, and LLPs for heterogeneous loans, respectively. $Treat$ equals one for banks that adopted CECL on January 1, 2020 and zero for banks that do not adopt CECL as of December 31, 2021. $Post$ equals one for bank-quarters after 2020, and zero otherwise. ΔNPL (-Homog./Hetero.) is the change in non-performing (homogeneous/heterogeneous) loans divided by beginning total loans. Standard errors reported in parentheses are clustered by bank. All variables are defined in Appendix A. *, **, and *** indicate statistical significance of the coefficients at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Dep. Var.	LLP_t	LLP_t (w/ Day 1)	LLP_t - Homog.	LLP_t - Hetero.
$Treat \times Post \times \Delta NPL_{t_+}$	0.320**	0.512***	-0.143	0.521***
	(0.125)	(0.145)	(0.438)	(0.149)
$Treat \times Post \times \Delta NPL_t$	0.229***	0.339***	0.299*	0.333*
	(0.073)	(0.095)	(0.173)	(0.201)
$Treat \times Post \times \Delta NPL_{t_-}$	-0.004	-0.046	0.397	-0.107
	(0.082)	(0.099)	(0.246)	(0.129)
$Treat \times \Delta NPL_{t_+}$	0.033	0.033	0.082	0.016
	(0.037)	(0.036)	(0.117)	(0.036)
$Treat \times \Delta NPL_t$	0.031	0.033	0.023	0.033
	(0.026)	(0.031)	(0.085)	(0.029)
$Treat \times \Delta NPL_{t_-}$	-0.049	-0.040	-0.261*	-0.002
	(0.045)	(0.045)	(0.155)	(0.027)
$Post \times \Delta NPL_{t_+}$	-0.007	-0.065	0.260	-0.331***
	(0.077)	(0.083)	(0.381)	(0.108)
$Post \times \Delta NPL_t$	-0.028	-0.029	0.073	-0.126
	(0.051)	(0.056)	(0.045)	(0.184)
$Post \times \Delta NPL_{t_-}$	0.068	0.094*	-0.190	0.234**
	(0.045)	(0.052)	(0.147)	(0.091)
ΔNPL_{t_+}	-0.009	-0.008	0.061**	-0.017
	(0.013)	(0.013)	(0.028)	(0.020)
ΔNPL_t	0.009	0.009	0.034	0.037**
	(0.011)	(0.011)	(0.033)	(0.016)
ΔNPL_{t_-}	0.027	0.027	0.095***	0.053***
	(0.018)	(0.018)	(0.036)	(0.018)
$Treat \times Post$	0.000	0.001***	0.000***	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	4,863	4,863	4,116	4,114
Bank FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Adj. Overall R-squared	0.576	0.542	0.581	0.399
Adj. Within R-squared	0.048	0.064	0.020	0.059

Table 3: Reflection of Local Economic Conditions in Provisions

This table reports the results of estimating the incorporation of local economic conditions in LLPs using Equation 2. The dependent variables in columns (1)–(4) are LLPs for all loans, LLPs with day-1 impact for all loans, LLPs for homogeneous loans, and LLPs for heterogeneous loans, respectively. $Treat$ equals one for banks that adopted CECL on January 1, 2020 and zero for banks that do not adopt CECL as of December 31, 2021. $Post$ equals one for bank-quarters after 2020, and zero otherwise. $\Delta CoIndex$ is the change in the weighted average of state-level coincident index based on banks' deposit shares in different states. Standard errors reported in parentheses are clustered by bank. All variables are defined in Appendix A. *, **, and *** indicate statistical significance of the coefficients at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Dep. Var.	LLP_t	LLP_t (w/ Day 1)	LLP_t - Homog.	LLP_t - Hetero.
$Treat \times Post \times \Delta CoIndex_{t_+}$	-0.035***	-0.065***	-0.017*	-0.029***
	(0.005)	(0.007)	(0.009)	(0.008)
$Treat \times Post \times \Delta CoIndex_t$	-0.016*	-0.016	-0.007	-0.026**
	(0.009)	(0.010)	(0.006)	(0.011)
$Treat \times Post \times \Delta CoIndex_{t_-}$	-0.021*	-0.016	-0.009	-0.026**
	(0.012)	(0.013)	(0.009)	(0.012)
$Treat \times \Delta CoIndex_{t_+}$	0.001	0.001	-0.001	-0.004**
	(0.001)	(0.001)	(0.001)	(0.002)
$Treat \times \Delta CoIndex_t$	-0.001	-0.007	0.000	0.013
	(0.009)	(0.010)	(0.006)	(0.009)
$Treat \times \Delta CoIndex_{t_-}$	0.008	-0.002	0.002	0.020
	(0.012)	(0.014)	(0.009)	(0.013)
$Post \times \Delta CoIndex_{t_+}$	0.035***	0.063***	0.033**	0.031***
	(0.007)	(0.012)	(0.015)	(0.009)
$Post \times \Delta CoIndex_t$	0.009	0.007	-0.000	0.016
	(0.008)	(0.009)	(0.006)	(0.010)
$Post \times \Delta CoIndex_{t_-}$	0.020**	0.014	0.010	0.024**
	(0.010)	(0.011)	(0.008)	(0.012)
$\Delta CoIndex_{t_+}$	-0.001	-0.002*	0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.002)
$\Delta CoIndex_t$	0.007	0.014	0.011*	-0.003
	(0.008)	(0.009)	(0.007)	(0.008)
$\Delta CoIndex_{t_-}$	-0.006	0.005	0.000	-0.018
	(0.010)	(0.012)	(0.008)	(0.012)
$Treat \times Post$	0.001***	0.001***	0.000***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	4,738	4,738	3,941	3,938
Bank FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Adj. Overall R-squared	0.581	0.564	0.563	0.408
Adj. Within R-squared	0.083	0.121	0.029	0.052

Table 4: LLP-related Disclosures

This table reports the results of estimating the increased LLP-related disclosure in banks' 10-Ks using Equation 3. The dependent variables in columns (1)–(3) are the natural logarithms of one plus the number of LLP-related sentences, LLP-related forward-looking sentences, and LLP-related quantitative sentences, respectively. *Treat* equals one for banks that adopted CECL on January 1, 2020 and zero for banks that do not adopt CECL as of December 31, 2021. *Post* equals one for bank-quarters after 2020, and zero otherwise. Standard errors reported in parentheses are clustered by bank. All variables are defined in Appendix A. *, **, and *** indicate statistical significance of the coefficients at the 10%, 5%, and 1% levels, respectively.

Dep. Var.	(1) *LLP Disc.*	(2) *LLP Disc.* - Fwd.	(3) *LLP Disc.* - Quant.
$Treat \times Post$	0.124***	0.201***	0.085**
	(0.028)	(0.037)	(0.041)
$Size_t$	0.152***	0.151**	0.205***
	(0.050)	(0.069)	(0.075)
$EBLLP_t$	0.568	-0.891	1.862*
	(0.642)	(1.082)	(0.982)
ΔNPL_t	-1.479	-1.932	-6.527*
	(2.475)	(3.810)	(3.326)
$Deposit_t$	-0.137	0.056	0.018
	(0.218)	(0.272)	(0.314)
$CapRatio_{t-1}$	0.189	0.865	0.165
	(0.434)	(0.730)	(0.614)
Observations	851	851	851
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adj. Overall R-squared	0.933	0.909	0.873
Adj. Within R-squared	0.055	0.058	0.019

Table 5: Loan-level Default

This table reports the results of estimating the decrease in loan-level default using Equation 4. *Treat* equals one for FR Y-14Q reporting banks that adopted CECL on January 1, 2020 and zero for FR Y-14Q reporting foreign banks that adopted IFRS 9 in 2018. *Post* equals one for bank-quarters after 2020, and zero otherwise. Observations start in 2018 to incorporate IFRS adoption of ECL. Standard errors reported in parentheses are clustered by bank. All variables are defined in Appendix A. *, **, and *** indicate statistical significance of the coefficients at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	*Default*	*Default*	*Default*	*Default*	*Default*	*Default*
Split. Vars.	All vs. New Loans		Private vs. Public Borrowers		High vs. Low PD	
$Treat \times Post$	-0.003**	-0.002*	-0.003**	-0.002	-0.003**	-0.001
	(-2.665)	(-1.899)	(-2.573)	(-1.412)	(-2.195)	(-1.050)
$Size_t$	0.000	0.002	0.002	-0.007*	0.001	0.000
	(0.187)	(1.064)	(0.679)	(-1.864)	(0.153)	(0.264)
$EBLLP_t$	0.200	0.364	0.207	0.320	0.358**	-0.119
	(1.623)	(1.395)	(1.595)	(1.309)	(2.519)	(-1.321)
$Deposit_t$	-0.001	-0.011	-0.001	0.018	-0.011	0.020*
	(-0.087)	(-0.670)	(-0.129)	(0.829)	(-1.199)	(1.920)
$CapRatio_{t-1}$	-0.016	0.066*	0.000	-0.071	-0.023	-0.014
	(-0.703)	(1.805)	(0.011)	(-1.567)	(-0.754)	(-0.630)
$Size^B$	-0.000	0.000	-0.000	-0.000	0.000	-0.000*
	(-0.769)	(1.258)	(-1.191)	(-0.697)	(0.149)	(-1.748)
$Leverage_t$	-0.001	0.004	-0.001	-0.001	-0.001	-0.000
	(-0.737)	(0.972)	(-0.588)	(-0.266)	(-0.562)	(-0.442)
Private	-0.002**	0.001			-0.002***	-0.001
	(-2.580)	(0.708)			(-2.940)	(-1.421)
PD_t	0.074***	0.005	0.074***	0.073*	0.075***	-0.091
	(6.635)	(0.224)	(7.133)	(1.757)	(7.072)	(-0.509)
$Maturity_t$	0.000	0.000**	-0.000***	0.000	0.000	0.000
	(0.612)	(2.444)	(-3.289)	(0.490)	(0.427)	(1.006)
Collateral	0.001**	0.001	-0.000	0.002***	-0.000	0.003***
	(2.511)	(0.701)	(-0.194)	(3.134)	(-0.346)	(3.331)
Guaranteed	-0.001	-0.001	-0.001	-0.001	-0.000	-0.002
	(-1.371)	(-1.234)	(-1.689)	(-0.840)	(-1.133)	(-1.410)
Syndicated	-0.005**	0.002	0.000	-0.013***	-0.003**	-0.007***
	(-2.730)	(0.738)	(0.043)	(-3.770)	(-2.261)	(-3.220)
New_t	-0.000		-0.001*	0.001	-0.001	-0.000
	(-0.960)		(-1.781)	(0.444)	(-1.290)	(-0.007)
Observations	708,785	33,204	593,112	115,239	482,494	223,147
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. Overall R-squared	0.136	0.374	0.163	0.087	0.166	0.075
Adj. Within R-squared	0.002	0.000	0.002	0.002	0.002	0.001

Table 6: CECL-induced Information Production: Timeliness

This table replicates Table 2, estimating the timeliness of LLPs using Equation 1 by comparing CECL banks with low- and high-CECL job postings to ILM banks. CECL jobs are calculated as the cumulative number of CECL-related job postings from 2017 to a given year-quarter. Large banks are CECL banks with above-median total assets in a given year-quarter. *Treat* equals one for banks that adopted CECL on January 1, 2020 and zero for banks that do not adopt CECL as of December 31, 2021. *Post* equals one for bank-quarters after 2020, and zero otherwise. ΔNPL is the change in non-performing loans divided by beginning total loans. Standard errors reported in parentheses are clustered by bank. All variables are defined in Appendix A. *, **, and *** indicate statistical significance of the coefficients at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	LLP_t			LLP_t (w/ Day 1)		
CECL Bank Split.						
CECL Jobs	Low	High	High	Low	High	High
Size	All	All	Large	All	All	Large
$Treat \times Post \times \Delta NPL_{t_+}$	0.325*	0.589***	0.747**	0.557***	0.870***	1.166***
	(0.168)	(0.226)	(0.307)	(0.199)	(0.266)	(0.338)
$Treat \times Post \times \Delta NPL_t$	0.140*	0.432***	0.454***	0.284**	0.557***	0.646***
	(0.073)	(0.110)	(0.119)	(0.128)	(0.125)	(0.141)
$Treat \times Post \times \Delta NPL_{t_-}$	-0.026	0.082	0.273	-0.013	0.023	0.274
	(0.102)	(0.164)	(0.190)	(0.119)	(0.208)	(0.216)
Observations	3,648	3,039	2,870	3,648	3,039	2,870
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj. Overall R-squared	0.540	0.593	0.601	0.513	0.534	0.544
Adj. Within R-squared	0.045	0.068	0.071	0.074	0.076	0.086

Table 7: CECL-induced Information Production: Local Economic Conditions

This table replicates Table 3, estimating the incorporation of local economic conditions in LLPs using Equation 2 by comparing CECL banks with low- and high-CECL job postings to ILM banks. CECL jobs are calculated as the cumulative number of CECL-related job postings from 2017 to a given year-quarter. Large banks are CECL banks with above-median total assets in a given year-quarter. $Treat$ equals one for banks that adopted CECL on January 1, 2020 and zero for banks that do not adopt CECL as of December 31, 2021. $Post$ equals one for bank-quarters after 2020, and zero otherwise. $\Delta CoIndex$ is the change in the weighted average of the state-level coincident index based on banks' deposit shares in different states. Standard errors reported in parentheses are clustered by bank. All variables are defined in Appendix A. *, **, and *** indicate statistical significance of the coefficients at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.		LLP_t			LLP_t (w/ Day 1)	
CECL Bank Split.						
CECL Jobs	Low	High	High	Low	High	High
Bank Size	All	All	Large	All	All	Large
$Treat \times Post \times \Delta CoIndex_{t_+}$	-0.027***	-0.047***	-0.049***	-0.053***	-0.078***	-0.086***
	(0.005)	(0.008)	(0.009)	(0.007)	(0.012)	(0.015)
$Treat \times Post \times \Delta CoIndex_t$	-0.024**	-0.016	-0.024	-0.029**	-0.022	-0.021
	(0.011)	(0.014)	(0.018)	(0.012)	(0.017)	(0.022)
$Treat \times Post \times \Delta CoIndex_{t_-}$	-0.029*	-0.018	-0.033	-0.032**	-0.017	-0.014
	(0.015)	(0.020)	(0.028)	(0.016)	(0.022)	(0.031)
Observations	3,507	2,885	2,708	3,507	2,885	2,708
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj. Overall R-squared	0.535	0.599	0.609	0.520	0.556	0.565
Adj. Within R-squared	0.055	0.116	0.126	0.102	0.145	0.157

Table 8: CECL-induced Information Production: LLP Disclosures

This table replicates Table 4, estimating the LLP-related disclosure using Equation 3 by comparing CECL banks with low- and high-CECL job postings to ILM banks. CECL jobs are calculated as the cumulative number of CECL-related job postings from 2017 to a given year-quarter. Large banks are CECL banks with above-median total assets in a given year-quarter. *Treat* equals one for banks that adopted CECL on January 1, 2020 and zero for banks that do not adopt CECL as of December 31, 2021. *Post* equals one for bank-quarters after 2020, and zero otherwise. Standard errors reported in parentheses are clustered by bank. All variables are defined in Appendix A. *, **, and *** indicate statistical significance of the coefficients at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep. Var.		*LLP Disc.*			*LLP Disc.* - Fwd.			*LLP Disc.* - Quant.	
CECL Bank Split.									
CECL Jobs	Low	High	High	Low	High	High	Low	High	High
Bank Size	All	All	Large	All	All	Large	All	All	Large
$Treat \times Post$	0.115***	0.133***	0.170***	0.183***	0.203***	0.241***	0.073	0.100*	0.129**
	(0.029)	(0.034)	(0.032)	(0.038)	(0.045)	(0.046)	(0.044)	(0.054)	(0.057)
Observations	483	361	307	483	361	307	483	361	307
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. Overall R-squared	0.954	0.963	0.976	0.921	0.946	0.953	0.916	0.922	0.930
Adj. Within R-squared	0.087	0.094	0.176	0.093	0.123	0.178	0.016	0.022	0.023

Table 9: CECL-induced Information Production: Loan-level Default

TThis table reports the results of estimating changes in loan-level default using Equation 4 by comparing Y-14Q reporting CECL banks with low- and high-CECL job postings to Y-14Q reporting foreign banks. CECL jobs are calculated as the cumulative number of CECL-related job positions from 2017 to a given year-quarter. Large banks are Y-14Q reporting CECL banks with above-median total assets in a given quarter. *Treat* equals one for FR Y-14Q reporting banks that adopted CECL on January 1, 2020 and zero for FR Y-14Q reporting foreign banks that adopted IFRS 9 in 2018. *Post* equals one for bank-quarters after 2020, and zero otherwise. Observations start in 2018 to incorporate IFRS adoption of ECL. Standard errors reported in parentheses are clustered by bank. All variables are defined in Appendix A. *, **, and *** indicate statistical significance of the coefficients at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
Dep. Var.	*Default*	*Default*	*Default*
CECL Bank Split.			
CECL Jobs	Low	High	High
Bank Size	All	All	Large
$Treat \times Post$	-0.002	-0.003**	-0.003*
	(-1.531)	(-2.281)	(-2.109)
Observations	217,679	480,021	392,723
Bank FE	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes
Loan Type FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Adj. Overall R-squared	0.193	0.123	0.093
Adj. Within R-squared	0.003	0.002	0.001

Online Appendix

Current Expected Credit Losses (CECL) Standard and Banks' Information Production

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This version: October 2022

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Figure OA.1: Loan Loss Provisioning around the Financial Crisis

This figure compares the average loan loss provisioning to beginning total loans of hypothetical groups of banks that would have been subject to CECL vs. banks that would have been exempt from CECL around the financial crisis period (2005–2010) had CECL been implemented then. Following the implementation of ASU 2016-13, we define CECL banks as public banks except for smaller reporting companies and ILM banks as smaller reporting companies and private banks as of 2007 Q4. We assume that the hypothetical adoption date is January 1, 2008, the onset of the financial crisis.

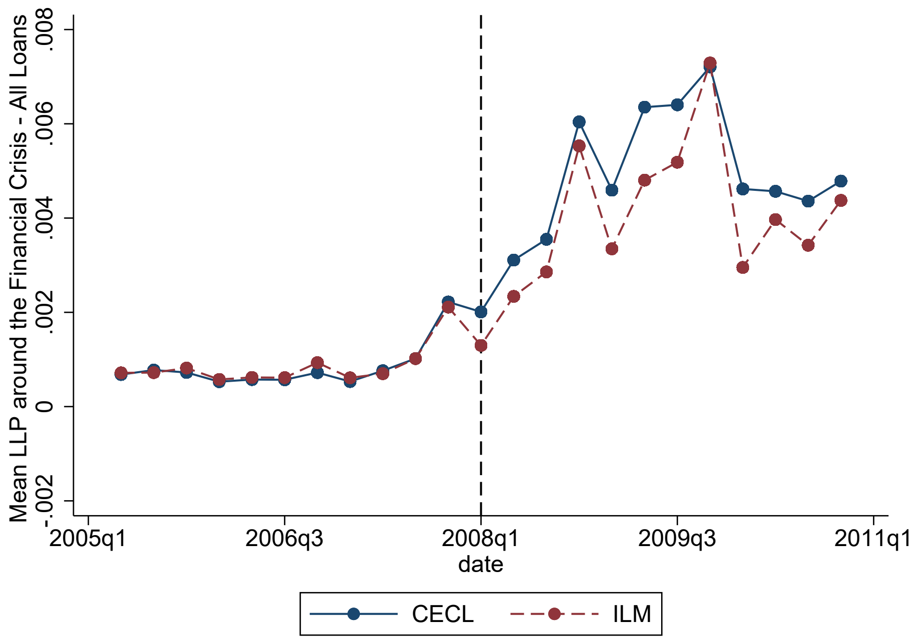
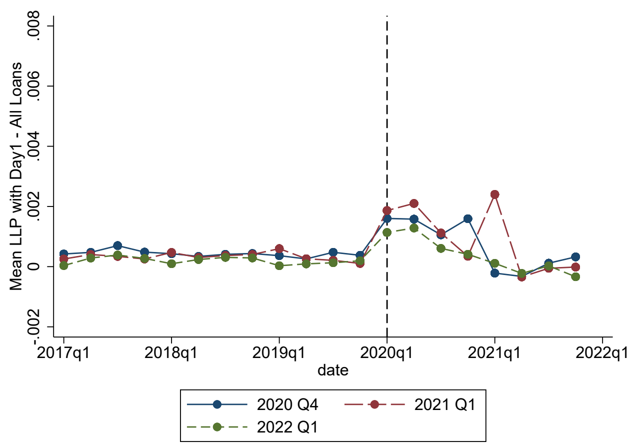


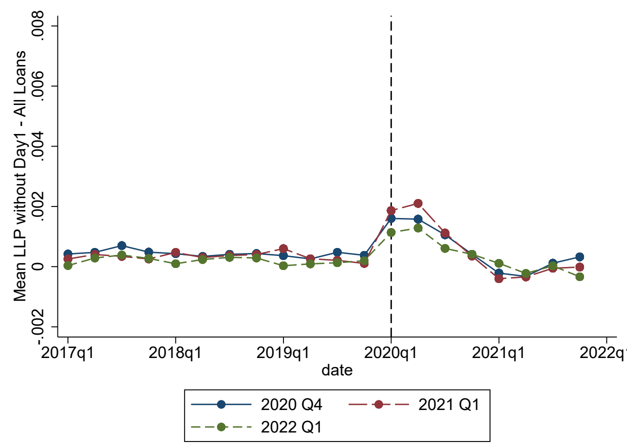
Figure OA.2: Loan Loss Provisioning by Delay Banks

This figure plots the average loan loss provisions to beginning total loans for banks that delayed CECL adoption under the Coronavirus Aid, Relief, and Economic Security (CARES) Act exemption and adopted CECL later. We divide the delayed adoption banks into three groups based on their delayed adoption date (2020 Q4, 2021 Q1, and 2022 Q1).Panel A reports LLPs with the day-1 impact for total loans. Panel B reports LLPs without the day-1 impact for total loans. Panel C reports LLPs for homogeneous loans. Panel D reports LLPs for heterogeneous loans. For homogeneous and heterogeneous loans, LLP is estimated as the change in allowance plus net charge-offs for each loan type.

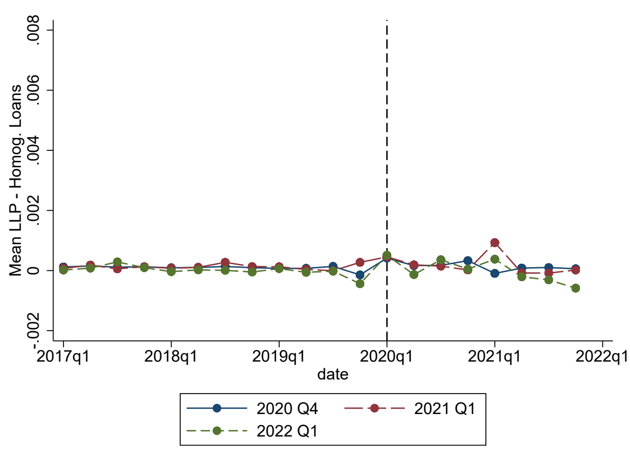
Panel A: LLP with Day1 - All Loans



Panel B: LLP without Day1 - All Loans



Panel C: LLP - Homog. Loans



Panel D: LLP - Hetero. Loans

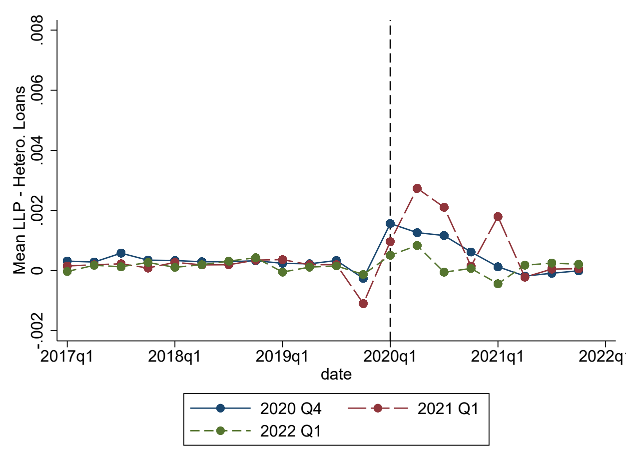


Table OA.1: Timeliness of Loan Loss Provisioning: Matched Sample

This table repeats the tests outlined in Equation 1 (Panel A) and Equation 2 (Panel B) of the paper using coarsened exact matching (CEM). With CEM, we coarsen the data by dividing observations into five evenly spaced bins of control variables (*Size*, *EBLLP*, *Deposit*, and $CapRatio_{t-1}$) so that CECL adopting and ILM banks have similar weighted histograms of these variables. Then, the weights are applied in a weighted least squares regression. All variables are defined in Appendix A of the paper. *, **, and *** indicate statistical significance of the coefficients at the 10%, 5%, and 1% levels, respectively.

Panel A: Timeliness of Loan Loss Provisioning

	(1)	(2)	(3)	(4)
Dep. Var.	LLP_t	LLP_t (w/ Day 1)	LLP_t - Homog.	LLP_t - Hetero.
$Treat \times Post \times \Delta NPL_{t_+}$	0.432***	0.617***	0.191	0.402**
	(0.159)	(0.169)	(0.369)	(0.185)
$Treat \times Post \times \Delta NPL_t$	0.112	0.231**	0.527***	0.089
	(0.081)	(0.111)	(0.171)	(0.152)
$Treat \times Post \times \Delta NPL_{t_-}$	-0.012	-0.058	0.497*	-0.018
	(0.100)	(0.126)	(0.284)	(0.163)
$Treat \times \Delta NPL_{t_+}$	0.035	0.037	0.127	-0.059
	(0.046)	(0.046)	(0.130)	(0.046)
$Treat \times \Delta NPL_t$	0.024	0.030	-0.070	0.007
	(0.037)	(0.041)	(0.101)	(0.041)
$Treat \times \Delta NPL_{t_-}$	-0.075	-0.060	-0.289	-0.024
	(0.061)	(0.061)	(0.188)	(0.070)
$Post \times \Delta NPL_{t_+}$	0.016	-0.031	0.126	-0.183
	(0.083)	(0.084)	(0.273)	(0.127)
$Post \times \Delta NPL_t$	0.054	0.054	-0.108	0.103
	(0.049)	(0.050)	(0.080)	(0.110)
$Post \times \Delta NPL_{t_-}$	0.093*	0.110**	-0.102	0.106
	(0.050)	(0.056)	(0.081)	(0.121)
ΔNPL_{t_+}	-0.005	-0.002	0.077***	0.040
	(0.018)	(0.018)	(0.024)	(0.032)
ΔNPL_t	0.018	0.019	0.110*	0.061**
	(0.025)	(0.025)	(0.065)	(0.031)
ΔNPL_{t_-}	0.052	0.053	0.127**	0.067
	(0.046)	(0.046)	(0.064)	(0.066)
$Treat \times Post$	0.000*	0.001***	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	4,022	4,022	3,310	3,314
Bank FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Adj. Overall R-squared	0.535	0.519	0.605	0.385
Adj. Within R-squared	0.063	0.090	0.048	0.051

Table OA.1: Timeliness of Loan Loss Provisioning: Matched Sample, continued

Panel B: Reflection of Local Economic Conditions in Provisions

	(1)	(2)	(3)	(4)
Dep. Var.	LLP_t	LLP_t (w/ Day 1)	LLP_t - Homog.	LLP_t - Hetero.
$Treat \times Post \times \Delta CoIndex_{t_+}$	-0.032***	-0.057***	-0.011***	-0.028***
	(0.005)	(0.007)	(0.004)	(0.008)
$Treat \times Post \times \Delta CoIndex_t$	-0.019*	-0.017	-0.015**	-0.019
	(0.011)	(0.012)	(0.006)	(0.013)
$Treat \times Post \times \Delta CoIndex_{t_-}$	-0.020	-0.011	-0.011	-0.027
	(0.014)	(0.015)	(0.009)	(0.023)
$Treat \times \Delta CoIndex_{t_+}$	0.002	0.002*	-0.002	-0.003
	(0.001)	(0.001)	(0.001)	(0.003)
$Treat \times \Delta CoIndex_t$	0.006	-0.001	0.010	0.008
	(0.010)	(0.011)	(0.006)	(0.012)
$Treat \times \Delta CoIndex_{t_-}$	0.012	-0.001	0.008	0.019
	(0.014)	(0.015)	(0.008)	(0.023)
$Post \times \Delta CoIndex_{t_+}$	0.023***	0.042***	0.010*	0.019*
	(0.007)	(0.011)	(0.005)	(0.010)
$Post \times \Delta CoIndex_t$	0.018*	0.013	0.003	0.016
	(0.010)	(0.010)	(0.006)	(0.012)
$Post \times \Delta CoIndex_{t_-}$	0.015	0.006	0.007	0.033
	(0.010)	(0.011)	(0.009)	(0.024)
$\Delta CoIndex_{t_+}$	-0.002	-0.003**	0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.003)
$\Delta CoIndex_t$	-0.008	-0.000	-0.000	-0.006
	(0.010)	(0.011)	(0.007)	(0.011)
$\Delta CoIndex_{t_-}$	-0.008	0.003	-0.005	-0.026
	(0.011)	(0.012)	(0.009)	(0.024)
$Treat \times Post$	0.001***	0.001***	0.000***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	3,864	3,864	3,098	3,102
Bank FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Adj. Overall R-squared	0.517	0.524	0.521	0.421
Adj. Within R-squared	0.080	0.132	0.042	0.075

Table OA.2: Loan Loss Provisioning around the Financial Crisis

This table compares the loan loss provisioning of hypothetical groups of banks that would have been subject to CECL vs. banks that would have been exempt from CECL around the financial crisis period (2005–2010) had CECL been implemented then. *Treat* equals one for public banks except smaller reporting companies as of 2007 Q4. *Post* equals one for bank-quarters after 2008, and zero otherwise. Panel A reports the results of estimating the timeliness of LLPs using Equation 1 of the paper. Panel B reports the results of estimating the incorporation of local economic conditions in LLPs using Equation 2 of the paper. All variables are defined in Appendix A of the paper. *, **, and *** indicate statistical significance of the coefficients at the 10%, 5%, and 1% levels, respectively.

Panel A: Timeliness of Loan Loss Provisioning

	(1)	(2)
Dep. Var.	LLP_t	LLP_t
Subsample	2006 - 2009	2005 - 2010
$Treat \times Post \times \Delta NPL_{t_+}$	-0.026	-0.035
	(0.040)	(0.036)
$Treat \times Post \times \Delta NPL_t$	-0.025	-0.011
	(0.042)	(0.038)
$Treat \times Post \times \Delta NPL_{t_-}$	0.017	0.015
	(0.053)	(0.045)
$Treat \times \Delta NPL_{t_+}$	0.038	0.026
	(0.033)	(0.030)
$Treat \times \Delta NPL_t$	0.055	0.043
	(0.036)	(0.034)
$Treat \times \Delta NPL_{t_-}$	0.059	0.033
	(0.040)	(0.039)
$Post \times \Delta NPL_{t_+}$	0.051**	0.049**
	(0.024)	(0.021)
$Post \times \Delta NPL_t$	0.037	0.019
	(0.026)	(0.022)
$Post \times \Delta NPL_{t_-}$	0.084***	0.064***
	(0.030)	(0.025)
ΔNPL_{t_+}	-0.023	-0.021
	(0.020)	(0.018)
ΔNPL_t	0.053**	0.054***
	(0.021)	(0.019)
ΔNPL_{t_-}	0.050**	0.059***
	(0.021)	(0.020)
$Treat \times Post$	0.000**	0.001***
	(0.000)	(0.000)
Observations	14,173	18,263
Bank FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Controls	Yes	Yes
Adj. Overall R-squared	0.483	0.451
Adj. Within R-squared	0.143	0.119

Table OA.2: Loan Loss Provisioning around the Financial Crisis, continued

Panel B: Reflection of Local Economic Conditions in Provisions

	(1)	(2)
Dep. Var.	LLP_t	LLP_t
Subsample	2006 - 2009	2005 - 2010
$Treat \times Post \times \Delta CoIndex_{t_+}$	0.000	0.000
	(0.020)	(0.016)
$Treat \times Post \times \Delta CoIndex_t$	0.026*	0.050***
	(0.016)	(0.014)
$Treat \times Post \times \Delta CoIndex_{t_-}$	0.000	-0.002
	(0.019)	(0.017)
$Treat \times \Delta CoIndex_{t_+}$	-0.003	0.004
	(0.019)	(0.014)
$Treat \times \Delta CoIndex_t$	-0.016	-0.041***
	(0.011)	(0.010)
$Treat \times \Delta CoIndex_{t_-}$	-0.031*	-0.019
	(0.016)	(0.015)
$Post \times \Delta CoIndex_{t_+}$	-0.026	-0.028*
	(0.017)	(0.015)
$Post \times \Delta CoIndex_t$	-0.018	-0.011
	(0.016)	(0.012)
$Post \times \Delta CoIndex_{t_-}$	0.030**	0.035**
	(0.015)	(0.015)
$\Delta CoIndex_{t_+}$	0.038**	0.031**
	(0.017)	(0.013)
$\Delta CoIndex_t$	0.004	-0.001
	(0.011)	(0.005)
$\Delta CoIndex_{t_-}$	-0.011	-0.032***
	(0.011)	(0.011)
$Treat \times Post$	0.000	0.001**
	(0.000)	(0.000)
Observations	13,310	17,976
Bank FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Controls	Yes	Yes
Adj. Overall R-squared	0.461	0.429
Adj. Within R-squared	0.123	0.099

Table OA.3: Understanding Banks Delayed CECL Adoption

This table provides various descriptive analyses of banks that delayed CECL adoption under the Coronavirus Aid, Relief, and Economic Security (CARES) Act exemption. Panel A reports the dates of delayed adoption. Panel B compares summary statistics of banks that adopted CECL as of January 1, 2020 to banks that delayed adoption. In Panel B, ΔNPL is in percentages. Panel C reports the estimation of a determinants model predicting the delay of CECL adoption. *Delay* equals one if the bank delayed CECL adoption under the CARES Act, and zero if the bank adopts CECL as of January 1, 2020. $CECL\ Est.$ equals one if the bank provides an estimation of day 1 adoption effects in their 10-K prior to 2020, and zero otherwise. $Homog\%$ is the percentage of homogeneous loan types divided by total loans. $Hetero\%$ is the percentage of heterogeneous loan types divided by total loans. All other variables are defined in Appendix A of the paper. *, **, and *** indicate statistical significance of the coefficients at the 10%, 5%, and 1% levels, respectively.

Panel A: Adoption Date by Delay Banks

Adoption Date	No. of Banks
2020 Q4	15
2021 Q1	18
2022 Q1	7
Merged	2
Total	42

Panel B: Descriptive Statistics

	(1)	(2)	(3)	(4)	(5)
	Delay		CECL		Diff. t-test
	Mean	P50	Mean	P50	t-stat
$Size$	8.534	8.516	9.962	9.605	-5.81***
$EBLLP$	0.006	0.006	0.009	0.006	-2.14**
$Deposit$	0.787	0.804	0.744	0.768	2.12**
$CapRatio$	0.119	0.117	0.127	0.124	-1.23
ΔNPL	-0.019	-0.008	0.005	0.001	-0.98
$Homog\%$	0.401	0.388	0.372	0.348	0.81
$Hetero\%$	0.579	0.579	0.542	0.574	0.99
$CECL\ Est.$	0.744	1.000	0.900	1.000	-2.60***
Obs.	39		150		

Table OA.3: Understanding Banks Delayed CECL Adoption, continued

Panel C: Determinants of Delaying CECL Adoption

	(1)	(2)	(3)
Dep Var.	Delay	Delay	Delay
Model	OLS	Logit	Probit
$CECL\ Est.$	-0.234***	-1.383**	-0.795**
	(0.086)	(0.625)	(0.367)
$Size$	-0.124***	-1.864***	-1.055***
	(0.023)	(0.405)	(0.222)
$EBLLP$	-8.923	-183.555*	-98.695*
	(5.930)	(110.555)	(58.914)
ΔNPL	-26.257	-148.581	-96.444
	(21.219)	(177.965)	(106.967)
$Deposit$	-0.480	-0.522	-0.061
	(0.334)	(3.588)	(2.180)
$CapRatio$	-1.878**	-1.241	-0.878
	(0.852)	(11.806)	(6.701)
$Homog\%$	-0.105	-0.344	-0.270
	(0.231)	(2.515)	(1.546)
$Hetero\%$	-0.226	-0.245	-0.231
	(0.244)	(2.593)	(1.601)
Constant	2.443***	18.545***	10.396***
	(0.513)	(5.250)	(3.026)
Observations	189	189	189
Adjusted R-squared	0.196		
Pseudo R-squared		0.324	0.325