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

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## Abstract

We examine whether the adoption of the current expected credit losses (CECL) model, which reflects forward-looking information in loan loss provisions, improves banks' information production. We find that CECL adopting banks' loan loss provisions are timelier and better reflect future local economic conditions. Consistent with these outcomes resulting from better information production, we find that CECL adopting banks have fewer loan defaults and disclose more forward-looking information after adopting CECL. In addition, the improvement in the quality of loan loss provisions is greater for banks that invest more in CECL-related information systems and human capital, a plausible channel for improved information production. Finally, CECL adopters' lending becomes less sensitive to economic uncertainty. 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

# 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 lives of loans 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]. Thus, understanding the impact of CECL adoption on banks' information production processes provides insights into how and why the CECL approach as an accounting standard could affect banks' real decision-making (e.g., lending). While banks are reasonably expected to exert more effort collecting, analyzing, organizing, and reporting information relevant to their loan portfolios under the CECL approach, such effects are empirically challenging to document for several reasons. Banks' information production activities on their borrowers are not directly unobservable to researchers.

[1]Accounting Standards Update (ASU) 2016-13 (ASC 326) has the effective implementation of January 1, 2020 (2023) for large public (small public and private) firms. FASB issued the new standard on June 16, 2016, see https://asc.fasb.org/imageRoot/39/84156639.pdf.

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

In addition, it is possible that CECL adoption may unlock forward-looking information *already* available internally and make it public through financial reporting without improving information production. We address these empirical challenges by utilizing novel loan-level data and identifying a plausible channel through which banks could increase information production: investment in information systems and human capital.

We study the impact of CECL adoption using U.S. bank holding companies (BHCs) data from 2017 to 2021. The sample includes three years prior to and two years after CECL implementation for large public banks. We apply 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 adoption under the Coronavirus Aid, Relief, and Economic Security (CARES) Act exemption.[3]

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 contain useful information about local economic conditions because banks collect detailed and proprietary information about the financial prospects of their customers [Khan and Ozel, 2016]. Thus, if banks produce better information about their customers and economic conditions, we expect banks' LLPs to reflect better future local economic conditions after CECL adoption.

Consistent with CECL adopting banks producing higher quality information, we find

[3]The CARES Act was signed into law in March 2020. Among public banks subject to CECL as of January 1, 2020, 46 banks elected to delay CECL adoption. As of January 1, 2022, 41 of these banks have adopted CECL.

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).

One potential concern regarding our LLP analyses is that two different mechanisms could explain our findings. First, banks might already have all the information, and CECL adoption only changes banks' reporting behavior without affecting their information production. Second, CECL adoption may prompt banks to exert more effort to produce forward-looking information about their customers and economic conditions. While these two mechanisms can coincide, we examine whether the second mechanism plausibly explains our findings using two additional tests.

First, we examine whether loan default decreases after CECL adoption. 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]. Research also suggests that 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 CECL adopting banks to exhibit fewer 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 those characteristics are mostly unobservable to researchers. We overcome these challenges by controlling for borrower-specific credit risks and loan-level characteristics, available in 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 exhibit fewer defaults on their loans than IHCs of foreign banks after CECL adoption. These results are more salient for private borrowers and riskier loans, consistent with the impact of information production being more sensitive for more opaque and riskier borrowers [Gustafson et al., 2021].

Second, we study whether CECL adopters provide more forward-looking disclosures following CECL adoption. Prior studies suggest that managers are reluctant to provide forward-looking information when their projections are uncertain [Waymire, 1985, Graham et al., 2005, Bozanic et al., 2018]. Forward-looking disclosure is also arguably independent of loan loss recognition. Hence, if banks produce better information for their loan portfolios and become more confident about these loan portfolios' prospects, we expect managers of CECL adopting banks to provide more forward-looking information in their financial reports. Consistent with this prediction, we find that the number of forward-looking words in CECL adopters' annual SEC 10-K filings increases for banks after CECL adoption. Overall, our findings on the loan-level defaults and forward-looking disclosures corroborate that CECL adoption improves banks' information production.

A natural follow-up question is through what channel CECL adopting 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. Following the approach in Acemoglu et al. [2022], we proxy for information systems and human capital investment using banks' job-postings data.[5] CECL-related job postings mainly contain three types of job functions:

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

[5] We acknowledge that banks can outsource CECL-related functions, including hiring consulting firms and purchasing credit models to prepare for CECL adoption. However, banks also have to maintain internal systems and have dedicated staff to comply with the CECL approach in their daily operations. Therefore, direct CECL-related hiring is likely to be a lower bound of CECL-related investments.

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.

Next, 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 have timelier LLPs, and their LLPs better reflect local economic conditions compared to banks with fewer CECL-related job postings. These effects are also more salient for larger banks. Overall, our analyses using the job posting data suggest that the investment in information systems and human capital is a plausible mechanism for capturing the impact of CECL adoption on 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].

Finally, we examine whether the improved information quality affects banks' lending decisions. Prior studies suggest that banks' information production largely affects their lending [Keys et al., 2010, 2012, Lisowsky et al., 2017]. On the one hand, if banks produce better information on their loan portfolios, their lending decisions can be less susceptible to economic uncertainty because they can better understand and evaluate potential risks. On the other hand, banks' lending decisions can be more sensitive to economic uncertainty when they possess better information if they want to avoid future risks by not making loans. Hence, whether banks' lending decisions become more or less sensitive to economic uncertainty is ultimately an empirical question. We use two proxies for economic uncertainty: the CBOE volatility index (VIX) and the Economic Policy Uncertainty (EPU) index developed by Baker et al. [2016]. We find that lending decisions by CECL adopting banks become less sensitive to economic uncertainty after CECL adoption. The result provides important policy implications as it suggests that banks with improved information due to CECL may reduce the likelihood of a credit crunch when economic uncertainty increases.

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 for the Post-Implementation Review (PIR). 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., 2022, Lu and Nikolaev, 2022]. Another stream of studies suggests that loan loss provisions 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 not only their reporting but also information production about their borrowers and underlying economic conditions. Thus, our findings suggest that accounting standards could be a useful tool for 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. Several 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

[Chen et al., 2019, Chatterjee, 2020, Christensen et al., 2021, Yoon, 2021]. 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 and Related Literature

## *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].

[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.

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]. Thus, under the CECL model, banks are expected to significantly update their information production process by collecting more information, investing more in information technology, and developing better forecasting models.

## *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 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., 2022, 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.

Another related strand of research examines the effects of the adoption of IFRS 9's 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 adoption, their findings may not be replicated under CECL adoption 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 that 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. Two potential explanations exist for these findings. First, CECL adoption may unlock forward-looking information already available internally and make it public through financial reporting. Second, CECL adoption may encourage banks to produce more forward-looking information about their customers and economic conditions. Prior studies do not differentiate between these two explanations. Our study differs from prior research because it examines whether the improved information contained in CECL allowances is driven by the better information production of the affected banks and the channels through which this effect might arise.

# 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. 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.[9] 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.[10] 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. FR Y-14Q data include commercial and

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

[9]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.

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

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 adopting banks in our sample.

Table 1 presents the descriptive statistics for our sample. Panel A provides the descriptive statistics for the bank-level sample in columns (1) through (8). 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.[11] 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, $lnAsset$, $EBLLP$, $Deposit$, and $CapRatio_{t-1}$, are significantly different between the two groups. We include bank fixed effects in all our regressions to mitigate concerns that differences between the CECL and ILM banks may affect our tests. 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.

[11] Banks with assets under $5 billion are only required to report allowances by loan type semiannually after 2020.

Panel B presents descriptive statistics for our loan-level analysis. 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]

# 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 (i.e., com-

[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. Our findings are also robust to using the natural logarithm of loan maturity instead.

mercial real estate, construction, and commercial and industrial loans) than homogeneous loans (i.e., residential and consumer loans) for several reasons. Banks primarily evaluate credit losses for homogeneous loans at the portfolio level and typically record LLPs in the amount of expected loan charge-offs over the next 12 months. Depending on the type of homogeneous loan, 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 requires 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 adopting banks increased LLPs significantly in 2020 Q1. This immediate jump is composed of the day-1 CECL adoption impact, which was estimated as of January 1, 2020, and additional upward adjustments during 2020 Q1, which reflects deteriorating economic conditions caused by the COVID-19 outbreak. However, their 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 adopting 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

[13]Banks do not report LLPs by loan type in 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

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.

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 use variations in the dependent variable. $LLP(w/Day1)$ adds the day-1 impact that bypasses the income statement.[14] $LLP - Homogeneous$ and $LLP - Heterogeneous$ 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

impact is included in LLPs by loan type.

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

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. We follow prior literature and include a number of control variables. In particular, $X_{i,t}$, includes $lnAsset_{i,t}$, the natural logarithm of total assets, $EBLLP_{i,t}$, the earnings before the loan loss provision 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, $\delta_t$, to control for economic conditions affecting all banks in each sample quarter and bank fixed effects, $\gamma_i$, 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 adopting 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 adopting 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

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

prediction that the improvement in information production would be more substantial for loans requiring more borrower-specific information.[16]

Next, we examine whether CECL adopting banks' LLPs contain more information about local economic conditions 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. The dependent variable, $LLP_{i,t}$, is the bank's loan loss provision divided by lagged total loans. Same as before, we also use variations in the dependent variable. $LLP(w/Day1)$ adds the day-1 impact that bypasses

[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., 2022]. Consistent with our findings in Table 2, we find stronger CECL impacts for banks with high proportions of heterogeneous loans.

[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.

the income statement. $LLP - Homogeneous$ and $LLP - Heterogeneous$ are calculated as the quarterly change in allowance plus net charge offs for homogeneous and heterogeneous loans. 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, 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, $\delta_t$, and bank fixed effects, $\gamma_i$, 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 $Treat_i \times Post_t \times \Delta CoIndex_{s,t_+}$ is significantly negative (-0.035, $p$ <0.01), suggesting CECL adopting banks' LLPs reflect changes in future local economic conditions better than ILM banks' LLPs after CECL adoption. 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 adopting 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

[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.

because macroeconomic indicators, which are correlated with local economic conditions, are important inputs to determine LLPs for both homogeneous and heterogeneous loans.

Before we move on to the next analyses, we conduct the coarsened exact matching (CEM) analyses for the LLP analyses to mitigate concerns that bank-characteristic differences between CECL adopting and ILM banks may affect our inferences. With CEM, we coarsen the data by dividing observations into five evenly spaced bins of all continuous control variables, 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. In untabulated analyses, we find the regression coefficients and their statistical significance largely stay similar to the analyses without matching. In addition, we also conduct the analyses by limiting the sample from 2018–2021 to make pre- and post-CECL periods balanced. Again, we find the regression coefficients and their statistical significance largely stay similar. These additional tests suggest that our findings are robust to different model specifications and sample compositions.

## *4.2 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 use two additional tests to examine whether the second mechanism plausibly explains our findings.

First, we examine whether loan-level default, observable in confidential FR Y-14Q regulatory filings, decreases after CECL adoption. 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 adopting 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 adopting 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:

$$Default_{i,j,k,t} = \beta_1 Treat_i \times Post_t + X_{i,t} + Y_{j,t} + Z_{k,t} + \delta_t + \gamma_i + \theta_j + \kappa_k + \epsilon_{i,j,k,t}, \tag{3}$$

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 within four quarters of the reporting quarter.[19] The same set of bank characteristics, as in Equation 2, are

[19]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.

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, an indicator variable for whether a given loan is newly originated, 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, and guaranteed.[20] Finally, we include year-quarter, $\delta_t$, bank, $\gamma_i$, borrower, $\theta_j$, and loan-type fixed effects, $\kappa_k$.

Table 4 reports the estimation of Equation 3. 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 adopting 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. 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.

Second, we examine whether managers at adopting banks provide more forward-looking disclosures after CECL adoption. Prior studies suggest that managers are reluctant to provide forward-looking information when projections are uncertain [Waymire, 1985, Graham et al., 2005, Bozanic et al., 2018]. Thus, if banks produce better information on their loan

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

portfolios and become more confident about economic forecasts, we expect managers at CECL adopting banks would provide more forward-looking statements in their financial reporting after CECL adoption.

We focus on forward-looking expressions in banks' public financial statements rather than managers' tendency to provide earnings forecasts because management guidance is rare in the banking industry. We create the word list containing forward-looking information in banks' 10-K filings following prior studies [e.g., Bozanic et al., 2018].[21] Thus, in the analysis of forward-looking statements, we focus on public banks that report 10-K/Q filings to the Securities and Exchange Commission (SEC).[22] We create the measure of forward-looking information contained in the entirety of 10-K filings, management discussion and analysis (MD&A) section of 10-K filings, and LLP-related content of 10-K filings.[23]

Figure 2 plots the average proportion of forward-looking words in 10-K filings, MD&A section, and LLP-related contents from 2017 to 2021. As LLPs in Figure 1, both groups' forward-looking words show clear parallel trends until CECL adoption. However, consistent with our prediction, the average proportion of forward-looking words increases for CECL adopting banks compared to ILM banks after CECL adoption in all three specifications.

We formally test this hypothesis using the following model:

$$FLWords_{i,t} = \beta_1 Treat_i \times Post_t + \beta_2 X_{i,t} + \delta_t + \gamma_i + \epsilon_{i,t}, \tag{4}$$

[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", "target". Next, we expand the list using word embedding. The 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 "aim", "assumption", "baseline", "deem", "future", "goal", 'judgement", "outlook", "probably/probability", "scenario", "uncertain(ty)", "(un)predictable".

[22] The control group is smaller reporting companies defined by the SEC, which are subject to CECL from January 2023.

[23] To identify sections of the 10-K related to LLPs, we first search for sentences which contain LLP-related words like "provision", "allowance", "default", "charge off", "credit loss", "loan loss". Next, we take the union of all sentences to locate within the $[-3, +3]$ window of the direct LLP-related sentences identified in the previous step. Before searching for patterns, we normalize raw filings to take care of punctuation, inflections, and extra white spaces.

where $i$ and $t$ index bank and year-quarter, respectively. The dependent variable is, $FLWords_{i,t}$, the number of forward-looking words divided by the number of total words in a bank's 10-K filings (or relevant sections). The same set of bank characteristics, as in Equation 2 are included. Finally, year-quarter fixed effects, $\delta_t$, and bank fixed effects, $\gamma_i$, are included.

Table 5 reports the estimation of Equation 4. In columns (1) through (3), we find that the coefficient on $Treat_i \times Post_t$ is significantly positive in all columns (0.001, $p$ <0.01; 0.002, $p$ <0.01; 0.003, $p$ <0.01). The results suggest that managers at CECL adopting banks provide more forward-looking information than those at ILM banks after CECL adoption, consistent with the prior studies showing managers tend to provide more forward-looking information when they are confident about their forecasts.

## *4.3 Potential Mechanism*

A natural follow-up question is through which channels CECL adopting 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 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.[24]

[24] Again, before searching for patterns, we normalize raw job postings to take care of punctuation, inflections, and extra white spaces.

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. Consistent with our prediction, CECL adopting 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 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.

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.[25] Also, smaller banks have argued, and regulators have acknowledged that CECL adoption is more burdensome for smaller banks.

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.

[25] 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.

In Panel C, we categorize these jobs based on the O*NET Standard Occupational Classification (SOC), which we obtain from LinkUp.[26] The SOC-based job titles and key tasks suggest that CECL jobs are mainly associated with three functions. First is managerial jobs related to managing relationships with customers 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 are generally related to banks' information production process, i.e., 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 adopting banks that made large vs. small investments in 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, studies suggest 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].[27]

Table 6 reports the estimation of Equation 1 by comparing banks with low CECL jobs and high CECL jobs 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 banks, high CECL job banks, and high CECL jobs & large banks, respectively. We find

[26] 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.*

[27] 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.

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 banks and the largest for large banks with high CECL jobs. 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. 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].[28]

Table 7 reports the estimation of Equation 2 by comparing banks with low CECL jobs and high CECL jobs 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 jobs and large 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.[29]

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].

[28] 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 banks only for heterogeneous loans.

[29] 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 banks and large banks for both homogeneous and heterogeneous loans.

## 4.4 Lending Sensitivity to Economic Uncertainty

Finally, we examine whether the improved information production affects banks' lending decisions. Prior studies suggest that banks' information production largely affects their lending decisions [Keys et al., 2010, 2012, Lisowsky et al., 2017]. If banks produce better information on their loan portfolios, their lending decisions can be less prone to economic uncertainty because they understand the potential risks better. On the other hand, other studies suggest that bank lending slows down when uncertainty in the economy is high [Bordo et al., 2016, Gissler et al., 2016, Hu and Gong, 2019]. If banks want to avoid risks by not making loans, their lending decisions can be more sensitive to economic uncertainty when they possess a higher quality of information. Hence, whether banks become more or less sensitive to economic uncertainty is ultimately an empirical question. We use two proxies for economic uncertainty, which are widely employed in the literature, the CBOE volatility index (VIX) and the Economic Policy Uncertainty (EPU) index developed by Baker et al. [2016]. We formally test this hypothesis using the following model:

$$\begin{aligned}\Delta Loan_{i,t} =& \beta_1 Treat_i \times Post_t \times Uncertainty_t + \beta_2 Treat_i \times Post_t \\ &+ \beta_3 Treat_i \times Uncertainty_t + \beta_4 X_{i,t} + \delta_t + \gamma_i + \epsilon_{i,t},\end{aligned} \tag{5}$$

where $i$ and $t$ index bank and year-quarter, respectively. The dependent variable is, $\Delta Loan_{i,t}$, the change in a bank's loan balances excluding PPP loans divided by lagged total loans. For the economic uncertainty, $Uncertainty_t$, we use two proxies: log(VIX) and log(EPU) index. The explanatory variables of interests are $Treat_i \times Post_t \times \Delta CoIndex_{s,t_+}$ and $Treat_i \times Post_t \times Uncertainty_t$, and we expect a positive (negative) coefficient if banks' lending decision becomes less (more) sensitive to the economic uncertainty. The same set of bank characteristics, as in Equation 2 are included. Finally, year-quarter fixed effects, $\delta_t$, and bank fixed effects, $\gamma_i$, are included.

Table 8 reports the estimation of Equation 5. In columns (1) through (3), we use the logarithm of the VIX index as a proxy for the economic uncertainty. In column (1), we find that the coefficient on $Treat_i \times Post_t \times \ln(VIX)_t$ is statistically positive (0.019, $p$ <0.05), suggesting that lending decisions by CECL adopting banks become less sensitive to economic uncertainty after CECL adoption. We also further examine the effects of CECL adoption on homogeneous and heterogeneous loans. In columns (2) and (3), we find that the coefficient on $Treat_i \times Post_t \times \ln(VIX)_t$ is statistically insignificant (-0.002, $p$ >0.10) for homogeneous loans, but significantly positive (0.015, $p$ <0.01) for heterogeneous loans. In columns (4) through (6), we use the logarithm of the EPU index as a proxy for the economic uncertainty. We only find a weakly significant coefficient (0.011, $p$ <0.10) for heterogeneous loans.[30] Overall, these results indicate that CECL adopting banks become less sensitive to economic uncertainty after CECL adoption, and this effect is more salient for heterogeneous loans than homogeneous loans.

# 5 Conclusion

We examine whether the adoption of the CECL model for loan loss provisioning improves banks' information production. We find that after CECL adoption, banks' loan loss provisioning becomes timelier and better reflects local economic conditions. Consistent with banks producing better information under the CECL approach, we also find that banks experience fewer loan-level default and provide more forward-looking information in their 10-K filings after CECL adoption. In addition, timelier loan loss provisioning and better reflection of local economic conditions are more salient for banks that posted more CECL-related jobs, suggesting that the investment in information systems and human capital is a plausible mechanism for the improved information production. Finally, benefiting from the improved information production, we find that lending becomes less sensitive to economic uncertainty

[30] Alternatively, we use changes in the VIX and EPU indexes to proxy the economic uncertainty, and find similar results (untabulated).

after CECL adoption.

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 also suggest that accounting standards that require the collection and analysis of forward-looking information can induce banks to produce better information and apply better information in loan origination.

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 loan loss provisioning by CECL adopting 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 adopting 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 will be applied to small public banks and private banks that are 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 4, *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* - Homogeneous | 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* - Heterogeneous | 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. |
| $\Delta$*NPL* | Ending non-performing loans (NPL) (BHCK5526 before 2018 and BHCK1403 after 2018) minus beginning NPL divided by beginning total loans. |
| $\Delta$*NPL* - Homogeneous | Change in non-performing loans for residential and consumer loans divided by beginning total loans. |
| $\Delta$*NPL* - Heterogeneous | Change in non-performing loans for construction, commercial real estate, and commercial/industrial loans divided by beginning total loans. |
| $\Delta$*Loan* | Quarterly change in loans excluding PPP loans divided by beginning total loans. |
| $\Delta$*Loan* - Homogeneous | Quarterly change in residential and consumer loans divided by beginning total loans. |
| $\Delta$*Loan* - Heterogeneous | Quarterly change in construction, commercial real estate, and commercial/industrial loans excluding PPP 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. |

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| **Variable** | **Definition** |
|---|---|
| *Default* | Equals one if a loan defaults during the four quarters after the reporting quarter and zero otherwise. |
| ln*Asset* | Natural logarithm of banks' beginning total assets (BHCK2170) in millions. |
| *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). |
| ln *VIX* | Natural logarithm of the quarter-end CBOE Volatility Index, which is normalized based on the index at the beginning of 2017. |
| ln*EPU* | Natural logarithm of the quarter-end Economic Policy Uncertainty index from Baker et al. [2016], which is normalized based on the index at the beginning of 2017. |
| *Size* | 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. |
| *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 Loan* | Equals one if a loan is part of a syndicate as reported in the FR Y-14Q and zero otherwise. |
| *New Loan* | Equals one if a loan is originated in the quarter of reporting as reported in the FR Y-14Q and zero otherwise. |
| *Loan Maturity* | Loan maturity in years as reported in the FR Y-14Q. |
| *PD* | Probability of default for a given loan as reported in the FR Y-14Q. |
| *Private* | Equals one if a borrower is privately-held as reported in the FR Y-14Q and zero otherwise. |
| Low CECL Jobs | Banks with a below-median number of cumulative CECL-related job postings from 2017 up to a given year-quarter. |
| High CECL Jobs | Banks with an above-median number of cumulative CECL-related job postings from 2017 up to a given year-quarter. |
| Large Banks | Banks with an above-median total assets in a given year-quarter. |

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| **Variable** | **Definition** |
|---|---|
| *FLWords* - 10-K | The number of forward-looking words in a bank's 10-K normalized by the number of total words. |
| *FLWords* - MD&A | The number of forward-looking words in a bank's MD&A section of the 10-K normalized by the number of total words. |
| *FLWords* - LLP | The number of forward-looking words related to loan loss provisions in a bank's 10-K normalized by the number of total words. |

# 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.<br>-Analyze financial or operational performance of companies facing financial difficulties to identify or recommend remedies.<br>-Assess companies as investments for clients by examining company facilities.<br>-Collaborate on projects with other professionals, such as lawyers, accountants, or public relations experts.<br>-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.<br>-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.<br>-Recruit staff members.<br>-Prepare operational or risk reports for management analysis.<br>-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.<br>-Interview personnel and conduct on-site observation to ascertain unit functions, work performed, and methods, equipment, and personnel used.<br>-Analyze data and other information gathered to develop solutions or alternative methods of proceeding.<br>-Plan study of work problems, such as organizational change, communications, information flow, integrated production methods, inventory control, or cost analysis.<br>-Confer with personnel concerned to ensure successful functioning of newly implemented systems or procedures. |

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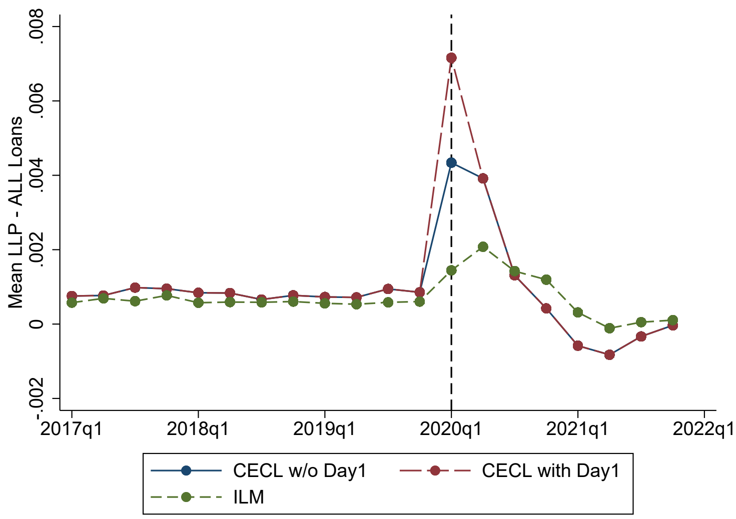
| SOC | Title | % of CECL Jobs | Top 5 Responsibilities |
|---|---|---|---|
| 13-2041.00 | Credit Analysts | 10.1% | -Analyze credit data and financial statements to determine the degree of risk involved in extending credit or lending money.<br>-Complete loan applications, including credit analyses and summaries of loan requests, and submit to loan committees for approval.<br>-Generate financial ratios, using computer programs to evaluate customers' financial status.<br>-Prepare reports that include the degree of risk involved in extending credit.<br>-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.<br>-Collect and analyze data on customer demographics, preferences, needs, and buying habits to identify potential markets and factors affecting product demand.<br>-Conduct research on consumer opinions and marketing strategies, collaborating with marketing professionals, statisticians, pollsters, and other professionals.<br>-Measure and assess customer and employee satisfaction.<br>-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.<br>-Report to management about asset utilization and audit results, and recommend changes in operations and financial activities.<br>-Collect and analyze data to detect deficient controls, duplicated effort, extravagance, fraud, or non-compliance with laws, regulations, and management policies.<br>-Inspect account books and accounting systems for efficiency, effectiveness, and use of accepted accounting procedures to record transactions.<br>-Supervise auditing of establishments, and determine scope of investigation required. |

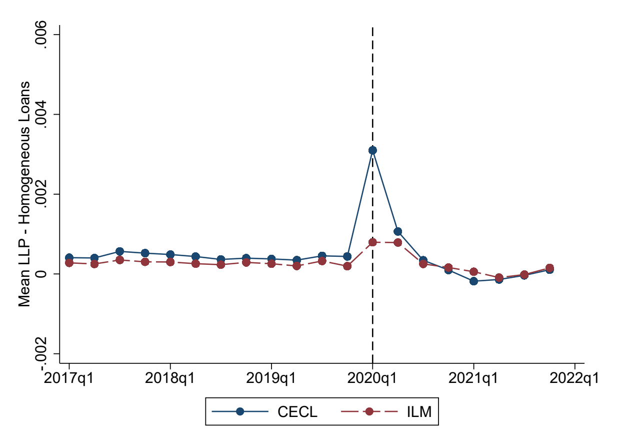
## Figure 1: Loan Loss Provisioning

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 is estimated as the change in allowance plus net charge-offs for each loan type.

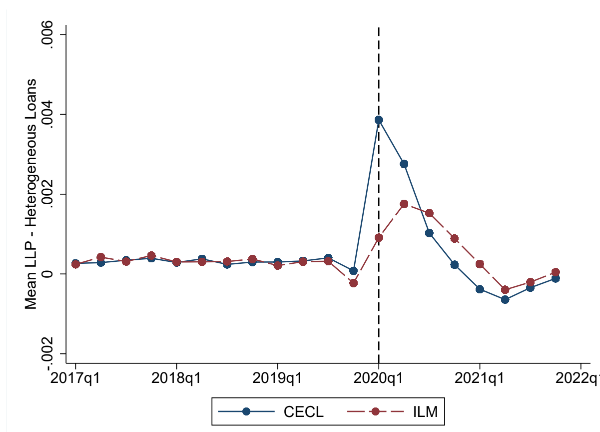
### Panel A: LLP - All Loans




### Panel B: LLP - Homog. Loans



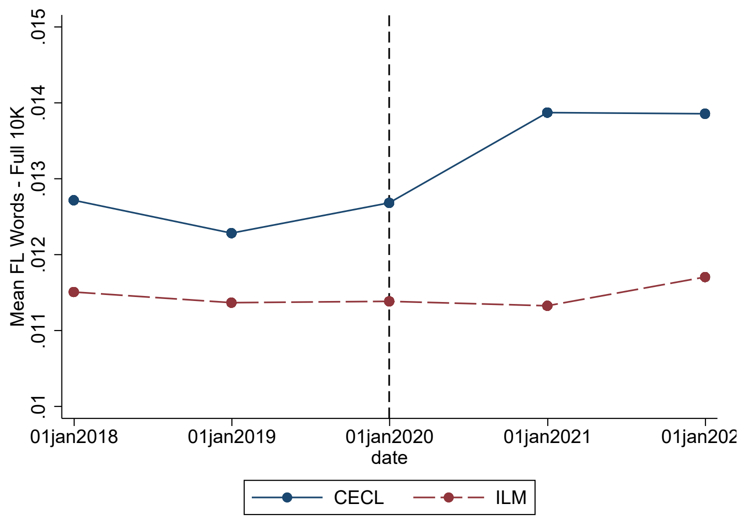

### Panel C: LLP - Hetero. Loans



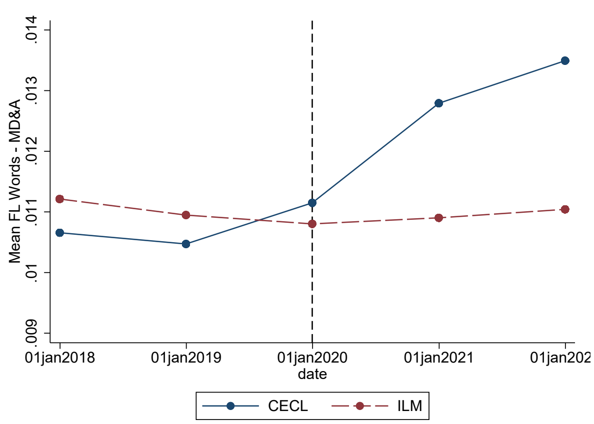
## Figure 2: Forward-looking Words in 10-K Filings

This figure plots the average forward-looking words divided by the total number of words in the relevant section (*FL Words*) by banks that adopted CECL on January 1, 2020 (CECL) and banks not subject to CECL adoption (ILM). Panel A, Panel B and Panel C report *FL Words* using the entirety of 10-K filings, MD&A sections of 10-K filings, and LLP-related content of 10-K filings, respectively.

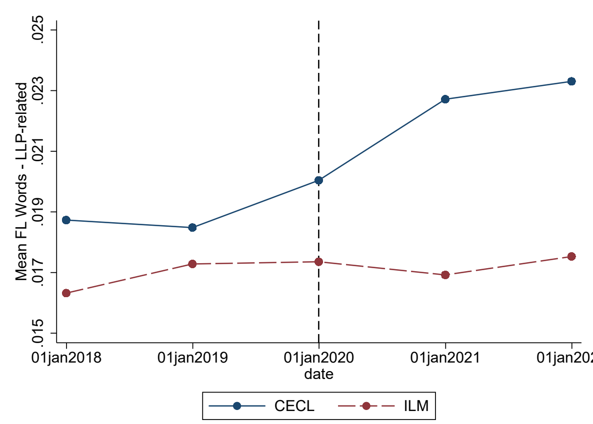
### Panel A: FL Words - Full 10-K




### Panel B: FL Words - MD&A




### Panel C: FL Words - LLP-related



## Figure 3: Time Trend 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 numbers for all industries and Panel B plots the numbers for banks only.

### Panel A: BLS Openings vs. Linkup Postings – All


### Panel B: BLS Openings vs. Linkup Postings – Banks

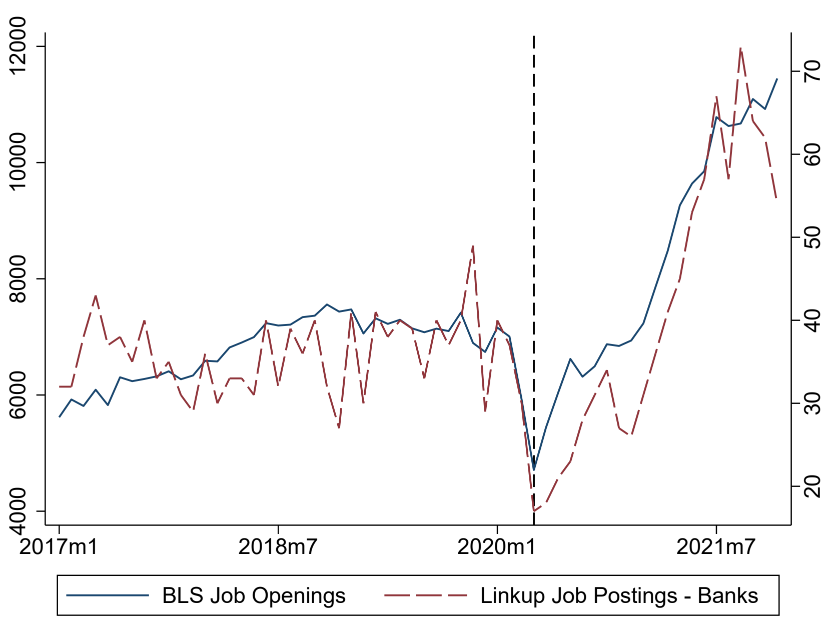
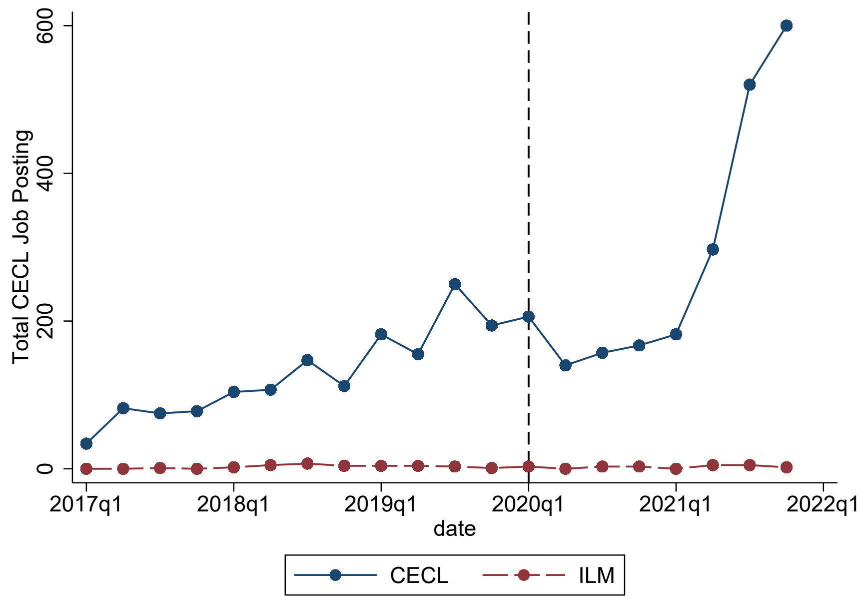


**Figure 4: Number of CECL-related Job Postings for CECL vs. ILM Banks**

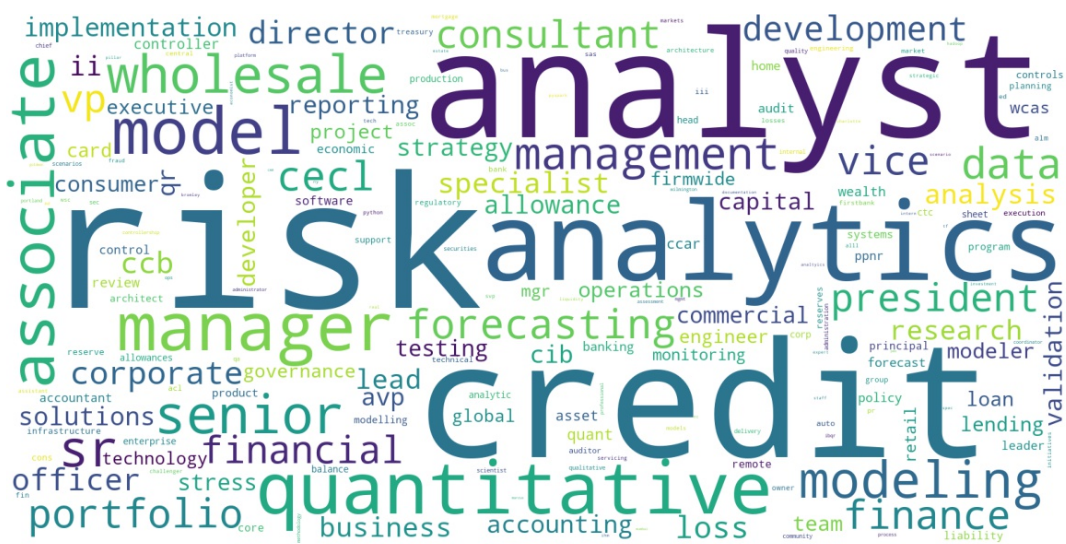
This figure plots the total number of CECL-related job postings on Linkup by banks that adopted CECL on January 1, 2020 (CECL) and banks not subject to CECL adoption (ILM)



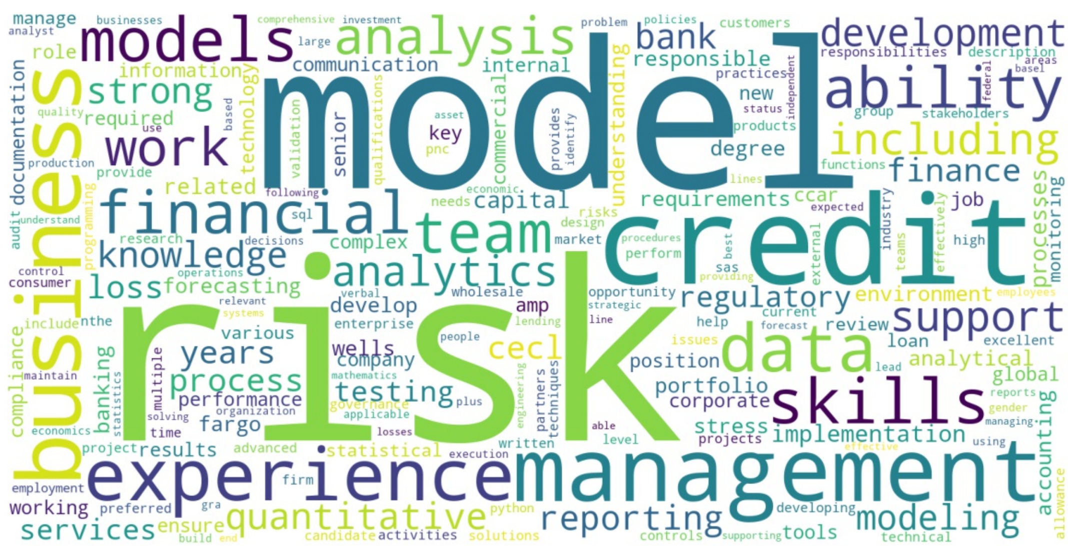
## Figure 5: Frequently Used Words in CECL-related Job Postings

This figure plots word clouds for the most frequently used words in CECL-related job postings. 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, $\Delta NPL$, and $\Delta Loan$ are in percentages. Panel A presents summary statistics for our bank-level analyses and Panel B presents summary statistics for 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 comparison banks (ILM or IHCs). All variables are defined in Appendix A. *, **, and *** indicate statistical significance of the mean differences at the 10%, 5%, and 1% levels, respectively.

### Panel A: Bank-Level Analyses

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Full Sample | | | | | | | | CECL Banks | | ILM Banks | | Two-sample $t$-test | |
| Firm chars. | N | Mean | Std. Dev. | 10th | 25th | Median | 75th | 90th | N | Mean | N | Mean | Diff. | $p$-value |
| *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 |
| $\Delta NPL$ | 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 |
| $\Delta NPL$ - Homog. | 5,488 | -0.000 | 0.061 | -0.038 | -0.014 | -0.001 | 0.010 | 0.037 | 2,941 | 0.001 | 2,547 | -0.001 | 0.001 | 0.423 |
| $\Delta NPL$ - Hetero. | 5,488 | 0.004 | 0.165 | -0.121 | -0.042 | -0.003 | 0.034 | 0.139 | 2,941 | 0.003 | 2,547 | 0.004 | -0.001 | 0.788 |
| $\Delta Loan$ | 5,488 | 2.337 | 5.701 | -1.690 | -0.171 | 1.300 | 3.174 | 6.153 | 2,941 | 2.488 | 2,547 | 2.163 | 0.325** | 0.035 |
| $\Delta Loan$ - Homog. | 5,488 | 0.713 | 2.577 | -1.072 | -0.336 | 0.266 | 1.050 | 2.678 | 2,941 | 0.703 | 2,547 | 0.725 | -0.022 | 0.750 |
| $\Delta Loan$ - Hetero. | 5,488 | 1.354 | 3.591 | -1.236 | -0.178 | 0.685 | 2.000 | 3.924 | 2,941 | 1.394 | 2,547 | 1.308 | 0.086 | 0.376 |
| $\Delta CoIndex$ | 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 |
| ln*Asset* | 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 |
| *FLWords* - Full | 850 | 0.013 | 0.002 | 0.010 | 0.012 | 0.013 | 0.014 | 0.015 | 724 | 0.013 | 126 | 0.011 | 0.002*** | <0.001 |
| *FLWords* - MD&A | 799 | 0.012 | 0.004 | 0.007 | 0.009 | 0.012 | 0.014 | 0.017 | 683 | 0.012 | 116 | 0.011 | 0.001* | 0.089 |
| *FLWords* - LLP | 850 | 0.020 | 0.004 | 0.015 | 0.017 | 0.020 | 0.023 | 0.026 | 724 | 0.021 | 126 | 0.017 | 0.004*** | <0.001 |

**Table 1: Descriptive Statistics, continued**

**Panel B: Loan-Level Analyses**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Full Sample | | | | | | | | CECL Banks | | IHCs | | Two-sample $t$-test | |
| Firm chars. | N | Mean | Std. Dev. | 10th | 25th | Median | 75th | 90th | N | Mean | N | Mean | Diff. | $p$-value |
| *Default* | 716,558 | 0.003 | 0.055 | 0 | 0 | 0 | 0 | 0 | 657,970 | 0.003 | 58,588 | 0.004 | -0.001*** | <0.001 |
| *lnAsset* | 716,558 | 13.163 | 1.143 | 11.768 | 12.040 | 13.037 | 14.469 | 14.486 | 657,970 | 13.211 | 58,588 | 12.630 | 0.581*** | <0.001 |
| *EBLLP* | 716,558 | 0.004 | 0.002 | 0.002 | 0.003 | 0.004 | 0.004 | 0.005 | 657,970 | 0.004 | 58,588 | 0.003 | 0.001*** | <0.001 |
| *Deposit* | 716,558 | 0.684 | 0.104 | 0.562 | 0.617 | 0.696 | 0.757 | 0.798 | 657,970 | 0.682 | 58,588 | 0.711 | -0.03*** | <0.001 |
| *CapRatio* | 716,558 | 0.129 | 0.017 | 0.108 | 0.113 | 0.129 | 0.137 | 0.151 | 657,970 | 0.126 | 58,588 | 0.157 | -0.031*** | <0.001 |
| *Size* | 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 |
| *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 Loan* | 716,558 | 0.188 | 0.391 | 0 | 0 | 0 | 0 | 1 | 657,970 | 0.189 | 58,588 | 0.179 | 0.009*** | <0.001 |
| *New Loan* | 716,558 | 0.068 | 0.252 | 0 | 0 | 0 | 0 | 0 | 657,970 | 0.070 | 58,588 | 0.045 | 0.025*** | <0.001 |
| *Loan 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 |
| *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 |
| *Private* | 716,558 | 0.838 | 0.368 | 0 | 1 | 1 | 1 | 1 | 657,970 | 0.836 | 58,588 | 0.863 | -0.027*** | <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. $\Delta NPL$ 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.

| VARIABLES | (1)<br>$LLP_t$<br>All Loans | (2)<br>$LLP_t$ (w/ Day 1)<br>All Loans | (3)<br>$LLP_t$<br>Homog. Loans | (4)<br>$LLP_t$<br>Hetero. Loans |
|---|---|---|---|---|
| $Treat \times Post \times \Delta NPL_{t_+}$ | 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) |
| $\Delta NPL_{t_+}$ | -0.009 | -0.008 | 0.061** | -0.017 |
| | (0.013) | (0.013) | (0.028) | (0.020) |
| $\Delta NPL_t$ | 0.009 | 0.009 | 0.034 | 0.037** |
| | (0.011) | (0.011) | (0.033) | (0.016) |
| $\Delta NPL_{t_-}$ | 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.

| VARIABLES | (1) $LLP_t$ All Loans | (2) $LLP_t$ (w/ Day 1) All Loans | (3) $LLP_t$ Homog. Loans | (4) $LLP_t$ Hetero. Loans |
|---|---|---|---|---|
| $Treat \times Post \times \Delta CoIndex_{t_+}$ | -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: Loan-level Default

This table reports the results of estimating the decrease in loan-level default using Equation 3. *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.

| VARIABLES | (1) *Default* All Loans | (2) *Default* New Loans | (3) *Default* Private Borrowers | (4) *Default* Public Borrowers | (5) *Default* High PD | (6) *Default* 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) |
| $lnAsset_t$ | 0.000 | 0.002 | 0.002 | -0.007* | 0.001 | 0.000 |
| | (0.187) | (1.064) | (0.679) | (-1.864) | (0.153) | (0.264) |
| $EBLLPt$ | 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) |
| $Size_t$ | -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) |
| *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 Loan* | -0.005** | 0.002 | 0.000 | -0.013*** | -0.003** | -0.007*** |
| | (-2.730) | (0.738) | (0.043) | (-3.770) | (-2.261) | (-3.220) |
| $New\ Loan_t$ | -0.000 | | -0.001* | 0.001 | -0.001 | -0.000 |
| | (-0.960) | | (-1.781) | (0.444) | (-1.290) | (-0.007) |
| $Loan\ Maturity_t$ | 0.000 | 0.000** | -0.000*** | 0.000 | 0.000 | 0.000 |
| | (0.612) | (2.444) | (-3.289) | (0.490) | (0.427) | (1.006) |
| $PD_t$ | 0.074*** | 0.005 | 0.074*** | 0.073* | 0.075*** | -0.091 |
| | (6.635) | (0.224) | (7.133) | (1.757) | (7.072) | (-0.509) |
| *Private* | -0.002** | 0.001 | | | -0.002*** | -0.001 |
| | (-2.580) | (0.708) | | | (-2.940) | (-1.421) |
| Observations | 708,785 | 33,204 | 593,112 | 115,239 | 482,494 | 223,147 |
| Bank FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year-Quarter FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Loan Type FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Borrower 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 5: Forward-looking Statements

This table reports the results of estimating the increased forward-looking statements in banks' 10-Ks using Equation 4. The dependent variables in columns (1)–(3) are the number of forward-looking words in the entirety of 10-K filings, MD&A sections of 10-K filings, and LLP-related content of 10-K filings, respectively, divided by the number of total words. $Treat$ 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.

| VARIABLES | (1)<br>$FLWords_t$<br>Full | (2)<br>$FLWords_t$<br>MD&A | (3)<br>$FLWords_t$<br>LLP |
|---|---|---|---|
| $Treat \times Post$ | 0.001*** | 0.002*** | 0.003*** |
| | (0.000) | (0.000) | (0.001) |
| $\ln Assets_t$ | 0.000 | 0.000 | 0.001 |
| | (0.000) | (0.001) | (0.001) |
| $EBLLP_t$ | -0.012 | -0.017 | -0.039 |
| | (0.012) | (0.022) | (0.033) |
| $\Delta NPL_t$ | 0.011 | 0.059 | -0.029 |
| | (0.023) | (0.055) | (0.058) |
| $Deposit_t$ | 0.002 | -0.000 | 0.011** |
| | (0.002) | (0.003) | (0.005) |
| $CapRatio_{t-1}$ | 0.000 | -0.007 | -0.001 |
| | (0.004) | (0.012) | (0.012) |
| Observations | 850 | 797 | 850 |
| Bank FE | Yes | Yes | Yes |
| Year-Quarter FE | Yes | Yes | Yes |
| Adj. Overall R-squared | 0.820 | 0.796 | 0.722 |
| Adj. Within R-squared | 0.084 | 0.051 | 0.086 |

## Table 6: CECL-induced Information Production: Timeliness

This table replicates Table 2, estimating the timeliness of LLPs using Equation 1 for subsamples of bank-quarters with below- vs. above-median CECL jobs. CECL jobs are calculated as the cumulative number of CECL-related job postings from 2017 to a given year-quarter. Large banks are 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. $\Delta NPL$ 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) |
|---|---|---|---|---|---|---|
| | $LLP_t$ | $LLP_t$ | $LLP_t$ | $LLP_t$ (w/ Day 1) | $LLP_t$ (w/ Day 1) | $LLP_t$ (w/ Day 1) |
| | All Loans | All Loans | All Loans | All Loans | All Loans | All Loans |
| | Low CECL Jobs | High CECL Jobs | High CECL Jobs | Low CECL Jobs | High CECL Jobs | High CECL Jobs |
| VARIABLES | All Banks | All Banks | Large Banks | All Banks | All Banks | Large Banks |
| $Treat \times Post \times \Delta NPL_{t_+}$ | 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 Condition

This table replicates Table 3, estimating the incorporation of local economic conditions in LLPs using Equation 2 for subsamples of bank-quarters with below- vs. above-median CECL jobs. CECL jobs are calculated as the cumulative number of CECL-related job postings from 2017 to a given year-quarter. Large banks are 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) |
|---|---|---|---|---|---|---|
| | $LLP_t$ | $LLP_t$ | $LLP_t$ | $LLP_t$ (w/ Day 1) | $LLP_t$ (w/ Day 1) | $LLP_t$ (w/ Day 1) |
| | All Loans | All Loans | All Loans | All Loans | All Loans | All Loans |
| | Low CECL Jobs | High CECL Jobs | High CECL Jobs | Low CECL Jobs | High CECL Jobs | High CECL Jobs |
| VARIABLES | All Banks | All Banks | Large Banks | All Banks | All Banks | Large Banks |
| $Treat \times Post \times \Delta CoIndex_{t_+}$ | -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: Lending Sensitivity to Economic Uncertainty

This table reports the results of estimating the sensitivity of loan growth to economic uncertainty using Equation 5. The dependent variable is quarterly loan growth, excluding PPP loans. $Treat$ 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. $\ln(VIX)$ is the natural logarithm of the quarter-end CBOE Volatility Index, which is normalized based on the beginning of the 2017 index. $\ln(EPU)$ is the natural logarithm of the quarter-end Economic Policy Uncertainty index from Baker et al. [2016], which is normalized based on the beginning of the 2017 index. 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.

| VARIABLES | (1)<br>$\Delta Loan_t$<br>All Loans | (2)<br>$\Delta Loan_t$<br>Homog. Loans | (3)<br>$\Delta Loan_t$<br>Hetero. Loans | (4)<br>$\Delta Loan_t$<br>All Loans | (5)<br>$\Delta Loan_t$<br>Homog. Loans | (6)<br>$\Delta Loan_t$<br>Hetero. Loans |
|---|---|---|---|---|---|---|
| $Treat \times Post \times \ln(VIX)_t$ | 0.019** | -0.003 | 0.015*** | | | |
| | (0.008) | (0.004) | (0.005) | | | |
| $Treat \times Post \times \ln(EPU)_t$ | | | | 0.015 | -0.001 | 0.011* |
| | | | | (0.010) | (0.004) | (0.006) |
| $Treat \times \ln(VIX)_t$ | -0.006 | -0.002 | -0.005 | | | |
| | (0.007) | (0.003) | (0.005) | | | |
| $Treat \times \ln(EPU)_t$ | | | | -0.002 | -0.003 | -0.003 |
| | | | | (0.009) | (0.004) | (0.006) |
| $Treat \times Post$ | -0.063** | 0.006 | -0.052*** | -0.087 | 0.004 | -0.066* |
| | (0.025) | (0.011) | (0.016) | (0.053) | (0.023) | (0.033) |
| $\ln Assets_t$ | 0.052*** | 0.025*** | 0.020*** | 0.052*** | 0.025*** | 0.020*** |
| | (0.009) | (0.004) | (0.006) | (0.009) | (0.004) | (0.006) |
| $EBLLP_t$ | -0.327* | -0.051 | -0.261** | -0.322* | -0.054 | -0.255** |
| | (0.176) | (0.047) | (0.110) | (0.176) | (0.047) | (0.110) |
| $\Delta NPL_t$ | 3.021*** | 0.925*** | 2.201*** | 3.022*** | 0.924*** | 2.204*** |
| | (0.558) | (0.254) | (0.322) | (0.559) | (0.254) | (0.322) |
| $Deposit_t$ | -0.072* | -0.008 | -0.016 | -0.073* | -0.008 | -0.017 |
| | (0.042) | (0.024) | (0.018) | (0.042) | (0.024) | (0.018) |
| $CapRatio_{t-1}$ | 0.016 | 0.014 | 0.013 | 0.017 | 0.014 | 0.014 |
| | (0.125) | (0.052) | (0.070) | (0.125) | (0.051) | (0.070) |
| Observations | 5,488 | 5,488 | 5,488 | 5,488 | 5,488 | 5,488 |
| Bank FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year-Quarter FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Adj. Overall R-squared | 0.130 | 0.105 | 0.155 | 0.130 | 0.105 | 0.154 |
| Adj. Within R-squared | 0.033 | 0.023 | 0.028 | 0.033 | 0.022 | 0.027 |