

Decision-Usefulness of Expected Credit Loss Information under CECL

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August 2022

We acknowledge helpful comments from Diana Choi, Alina Lerman, Karl Muller, Stephen Ryan, Hal Schroeder, Laura Wellman, Sunny Yang, Ying Zhou, Youli Zou, and workshop participants at the Pennsylvania State University, University of Connecticut, Midwest Accounting Research Conference, and University of Georgia.

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Abstract

The Financial Accounting Standards Board (FASB) recently replaced the “incurred loss” (IL) model of reporting credit losses with the “current expected credit loss” (CECL) model to improve the timeliness of credit loss information for financial statement users. CECL requires entities to recognize estimated lifetime credit losses upon loan origination, which is timelier than the IL model but potentially less accurate. We examine whether newly recognized credit losses under CECL (i.e., the CECL day-1 impact) are decision-useful for equity investors. We find that CECL day-1 impacts improve the value relevance of credit loss allowances and their predictive ability for future credit losses, and overall, that CECL allowances have greater value relevance and predictive ability than IL allowances. Furthermore, CECL day-1 impacts provide new information to investors, rather than only confirming expectations, which reduced investor uncertainty during the onset of the COVID-19 crisis.

As a result of the 2007–2009 financial crisis, policymakers adopted the view that credit loss recognition under the incurred loss (IL) accounting model was “too little, too late” (Dugan 2009; Financial Stability Forum 2009; Basel Committee on Banking Supervision [BCBS] 2011; Bischof, Laux, and Leuz 2021). The IL model precludes banks from recognizing credit losses that are not yet “probable”, a feature which some have argued amplified the depth and duration of the financial crisis (Financial Stability Forum 2009; BCBS 2021). In response to calls from investors, regulators, and G20 leaders for accounting standard setters to improve loan loss provisioning standards (Bernanke 2009; Financial Stability Forum 2009; G20, 2009), the FASB developed the current expected credit loss (“CECL”) model of credit loss recognition and issued the CECL standard in ASU 2016-13 in June 2016.¹ CECL requires entities to estimate and recognize lifetime expected credit losses at loan origination. Called the “most sweeping change to bank accounting ever” by the American Bankers Association,² CECL has generated considerable controversy and debate, including calls for further implementation delays or complete revocation of the standard.³

The FASB’s stated objective for CECL is to “provide financial statement users with more decision-useful information about the expected credit losses on financial instruments and other commitments to extend credit held by a reporting entity at each reporting date” (FASB 2016). A set of publicly-listed U.S. banks was required to adopt CECL for fiscal years beginning after December 15, 2019. Using contemporaneous credit loss information under both the IL and CECL standards, we examine the extent to which credit loss recognition under CECL provides information that is more decision-useful for equity investors than does the existing IL model.

¹ In 2014, the IASB issued an expected credit loss standard, IFRS 9 *Financial Instruments*, which typically recognizes only 12-month expected credit losses upon loan origination, whereas CECL recognizes lifetime expected credit losses upfront for all loans upon origination (see Section 2.2 for additional detail).

² See “*ABA Position*” on CECL (<https://www.aba.com/advocacy/our-issues/cecl-implementation-challenges>).

³ For example, some members of Congress (e.g., Rep. Blaine Luetkeyemer), banking trade groups (e.g., American Banker Association, Banking Policy Institute), and CEOs or CFOs of some large U.S. banks (e.g., Capital One, BB&T Corp.) all called for either a complete revocation or at least further implementation delays of CECL.

Two streams of academic literature offer insights related to our research question. First, academic literature on the timeliness of banks' credit loss recognition finds that timelier credit loss recognition disciplines bank risk-taking (e.g., Bushman and Williams 2012, 2015), presumably because the timelier information helps investors monitor banks' lending activities. This evidence is based on analyses of discretionary cross-country or cross-bank timeliness differences in credit loss recognition under the IL regime. Relative to these discretionary timeliness differences in the IL regime, CECL is an extreme form of timely credit loss recognition – all potential lifetime losses are recognized upon loan origination, much earlier than those considered by prior studies under the IL regime. Second, a stream of academic literature estimates expected credit losses and finds researcher-constructed estimates are useful in predicting future credit losses and bank failures (Harris, Khan, and Nissim 2018; Lu and Nikolaev 2021) and in pricing bank stocks (Wheeler 2021). Overall, because these studies find that (1) timelier credit loss recognition within the IL regime is beneficial for investors and (2) researcher-constructed expected credit loss estimates are useful for predicting future credit losses and/or pricing stocks, credit loss recognition under CECL is expected to be more decision-useful for equity investors than that under the IL model.

However, expected credit losses under CECL may not exhibit the properties predicted by prior research for several reasons. First, researcher-estimated expected losses likely differ from banks' own estimates of expected losses under CECL. For example, to estimate expected losses, Wheeler (2021) relies on estimated loan originations rather than actual originations and models credit losses using only one estimation method—vintage analysis; banks' own CECL implementation would utilize actual originations and could be based on different methods mentioned in FASB (2016, p. 109, para. 326-20-30-3), such as the loss-rate method on the

collective set of loans (Example 1 in FASB 2016, p. 129), roll-rate method, probability-of-default method, discounted cash flow method, or aging schedules.

Second, because CECL potentially trades off accuracy for timeliness (Mahieux, Sapra, and Zhang 2020), banks' lifetime expected credit loss estimates at origination may not be sufficiently accurate to be useful. CECL requires entities to estimate future credit losses based on managers' forecasts of future economic conditions, which could be heavily influenced by current economic conditions. Covas and Nelson (2018) suggest that banks could overestimate (underestimate) future credit losses during weak (strong) economic periods.

Third, banks' own estimates of expected credit losses under CECL could be biased due to strategic incentives, which are not considered in researcher-constructed estimates. Prior research finds that banks use discretion under the IL model to manage earnings and/or regulatory capital.⁴ While CECL removes discretion regarding when to recognize credit losses, it potentially increases the discretion in calculating the amount of lifetime credit losses to be recognized. CECL allows entities to use judgment in determining the relevant information and appropriate estimation methods, including: the length of a "reasonable and supportable" forecasting period; the factors forecasted; and how to weigh historical, current, and forecasted information to determine the allowance for credit losses.⁵ Overall, these three concerns highlight the difficulty in relying on prior research for predicting the actual effects of CECL implementation, and are consistent with the observation by prudential policymakers that "it is difficult to assess ex ante the impacts" of CECL (BCBS 2021).

⁴ See Section 5 of Beatty and Liao (2014) for a review of this literature.

⁵ For example, PNC Financial Services Group states in its 2019 10-K filing: "[O]ur loss estimates are sensitive to the shape and severity of macroeconomic forecasts and thus vary significantly between upside and downside scenarios. Changes to probability weights assigned to these scenarios and timing of peak business cycles reflected by the scenarios could materially affect our loss estimates."

According to the FASB’s Conceptual Framework, useful financial information is both relevant (i.e., has material predictive and/or confirmatory value), and faithfully representative (i.e., represents the phenomena that it purports to in a complete, neutral, and error-free manner) (FASB 2010b). The credit loss allowance under CECL purports to convey lifetime expected credit losses, in contrast to the IL allowance, which conveys only losses that have met the “probable” threshold of having been incurred. If CECL allowances are more relevant than IL allowances, they should better predict future losses or better confirm information that investors use in pricing the stocks. If CECL allowances are a faithful representation, they should be more related to factors that reflect lifetime expected losses, in a neutral manner, than IL allowances. Using data on 197 publicly listed U.S. banks that have adopted CECL, we identify the impact of the day-one application of CECL on banks’ credit loss allowances, i.e., the amount of credit losses incremental to the IL allowance that banks recognized to comply with the new standard (hereafter, “the CECL day-1 impact”). Examining the CECL day-1 impact allows us to provide evidence on the nature of this impact and the decision-usefulness of CECL information for equity investors.

We first examine the determinants of the CECL day-1 impact to test whether the impact is related to information that reflects lifetime expected credit losses. We divide the determinants into two groups: those related to potential future credit losses and those related to potential strategic estimation bias. We find that the proxies for potential future credit losses—the amount of nonperforming loans and the average interest rate charged on the loans—are positively associated with the CECL day-1 impact, such that the CECL allowance reflects loans' underlying riskiness to a greater extent than the IL allowance. As proxies for potential strategic bias in estimating credit loss reserves, we examine: (i) the extent to which the bank has a recent history of smoothing earnings via credit loss provisioning, and (ii) whether the bank’s tier 1 risk-based capital ratio is

in the bottom quintile (i.e., weakly capitalized relative to peers), and we find little evidence that the CECL day-1 impact is related to these measures of potential strategic bias.

We next assess the decision-usefulness of credit loss recognition and measurement under CECL for equity investors. First, we assess the extent to which the CECL day-1 impact is value relevant; specifically, whether the CECL day-1 impact has incremental explanatory power for stock prices beyond the IL allowance. As predicted, we find that the CECL day-1 impact has incremental explanatory power for stock prices beyond the IL allowance. Second, we assess the extent to which the CECL day-1 impact is predictive of future nonperforming loans and future net charge-offs beyond the IL allowance. As predicted, we find that the CECL day-1 impact incrementally predicts future nonperforming loans and future net charge-offs relative to the IL allowance, suggesting that CECL improves the timeliness of credit loss recognition. Taken together, the findings on determinants, pricing, and predictiveness are consistent with CECL allowances being more decision-useful for investors than IL allowances.

Our tests of value relevance do not address whether CECL day-1 impacts provide *new* information to investors or, instead, merely confirm expectations investors form prior to CECL using available information (e.g., Wheeler 2021). To address whether CECL day-1 impacts provide new information, we first examine investor response to revisions in banks' estimates of their expected CECL impact leading up to adoption. Using an event study research design around banks' quarterly earnings announcement/filing cycle, we find that revisions in banks' CECL estimates are negatively associated with bank stock returns in the quarterly reporting windows leading up to adoption, consistent with investors perceiving increases (decreases) in the estimates as bad (good) news that hadn't previously been impounded in stock prices.

As a second approach to examining whether CECL day-1 impacts provide new information to investors, we use the onset of the COVID-19 pandemic in late February 2020 as a shock that substantially increased both the level and uncertainty of expected credit losses. If CECL day-1 impact disclosures provide new information to investors, then the increase in uncertainty about future credit losses at the onset of COVID should not be as severe for the banks that already disclosed expected CECL day-1 impacts. Using a difference-in-differences design, we compare banks required versus not required to disclose expected CECL day-1 impacts before the onset of COVID. To address differences in bank size, we include polynomial size controls and conduct placebo tests. During the onset of COVID, banks required to disclose expected CECL day-1 impacts before the onset experience (1) smaller increases in information asymmetry and (2) smaller increases in stock illiquidity, relative to banks not required to provide such information before the onset. This finding is again consistent with expected CECL day-1 impacts providing new information for investors and reducing uncertainty about banks' potential future credit losses.

Our study makes two contributions. First, the academic literature has long been interested in the implementation and consequences of specific, major accounting standards.⁶ CECL and its international-standard counterpart, IFRS 9 *Financial Instruments*, are major standards and similarly merit examination. While a few recent studies that examine the consequences of the implementation of IFRS 9 (e.g., López-Espinosa, Ormazabal, and Sakasai 2021), CECL implementation in the U.S. merits specific examination due to the substantial differences between the two standards (see Section 2.2). To our knowledge, we provide the first empirical evidence on

⁶ For examples, researchers have specifically examined: SFAS 131 related to segment reporting requirements (e.g., Berger and Hann 2003; Botosan and Stanford 2005), SFAS 123 and 123R related to stock compensation expense (e.g., Aboody, Barth, and Kasznik 2004, 2006; Choudhary, Rajgopal, and Venkatachalam 2009; Barth, Gow, and Taylor 2012), and SFAS 161 requiring new disclosures about derivatives and hedging activities (e.g., Chen, Dou, and Zou 2021).

the impact of actual CECL implementation on banks' credit loss recognition and whether this information is useful to equity investors. Despite stakeholders' significant concerns during CECL's development and implementation, including that forecasting lifetime expected losses would be too difficult to be meaningful, our empirical evidence suggests that credit loss allowances under CECL are better predictors of future credit losses and more decision-useful for equity investors than those in the IL regime. Additionally, we provide evidence that CECL reduced information asymmetry and mitigated increases in stock illiquidity during the onset of COVID-19 by providing new information about lifetime expected credit losses.

Second, we contribute to the academic literature on credit loss recognition timeliness. This literature suggests that timelier recognition under the IL regime helps equity investors discipline bank risk-taking by providing more useful information (e.g., Beatty and Liao 2011; Bushman and Williams 2012, 2015). Because CECL requires the recognition of lifetime expected losses on the day of loan origination, the implementation of CECL represents an even timelier recognition of credit losses than has been examined in prior research. While several recent studies develop models to estimate lifetime expected credit losses and find that their estimates are useful for predicting future credit losses and bank failure (Harris et al. 2018; Lu and Nikolaev 2021) and for pricing stocks (Wheeler 2021), we provide evidence related to banks' own estimates of lifetime expected credit losses upon CECL adoption and the relevance of this information. Additionally, we find that banks' own estimates of expected credit losses provide investors with new information, which has not been shown in prior research.

2. Background

2.1. Institutional Details about CECL and IL Models

Prior to CECL, accounting for credit losses followed ASC 450-20 (formerly SFAS 5) for loans not individually identified as impaired and ASC 310-10-35 (formerly SFAS 114) for loans

individually identified as impaired. Most credit losses were covered by ASC 450-20 and treated as loss contingencies, wherein credit losses were recognized only when losses were “probable” and “reasonably estimable”. The accounting treatments prior to CECL are commonly referred to as the “incurred loss” (IL) model. As noted by the FASB, financial statement users criticized the IL model because (1) the “probable” threshold delayed recognition of credit losses that were expected but did not meet the threshold, and (2) diversity in entities’ determination of “probable” made it difficult to compare losses across entities (FASB 2016, para. BC3–BC7).

ASU 2016-13 “Measurement of Credit Losses on Financial Instruments” (FASB 2016) removes the “probable” threshold and requires banks to estimate and record a reserve for lifetime expected credit losses on loans at the time of loan origination. CECL applies principally to financial instruments measured at amortized cost, including loans held for investment, held-to-maturity (HTM) debt securities, purchased credit-deteriorated (PCD) assets, and trade receivables, as well as off-balance-sheet credit exposures (e.g., unfunded loan commitments).⁷ Loans are by far the most significant financial instrument class for a typical bank, and thus the most economically significant impact of CECL for a typical bank is on its loans held for investment. Under this new standard, entities are required to measure expected credit losses for loans based on relevant information about past events, current conditions, and reasonable and supportable forecasts of factors that could affect the collectability of the reported amount. The incorporation of reasonable and supportable forecasts of factors that could affect the collectability under CECL is new; under

⁷ For PCD assets, CECL requires an initial allowance for lifetime credit losses to be established when the asset is purchased and also added to the gross recorded balance of the asset. This gross-up approach increases the overall allowance and the PCD asset balance by the same amount, without affecting retained earnings. For available-for-sale (AFS) debt securities, entities are required to assess AFS debt securities for credit losses and record any identified credit losses through credit loss allowances rather than direct write-downs.

the IL model, an entity generally considered only past events and current conditions in measuring the incurred loss (FASB 2016, p. 3).

An entity's required CECL adoption date depends on whether the entity is considered a smaller reporting company (SRC) by the SEC.⁸ Non-SRC public business entities were required to adopt CECL in fiscal years beginning after December 15, 2019, including interim periods within those fiscal years. SRCs were required to adopt CECL for fiscal years beginning after December 15, 2022. The Coronavirus Aid, Relief, and Economic Security ("CARES") Act, passed on March 25, 2020 and signed into law two days later, provided non-SRCs with the option to delay CECL adoption until 2021. For those non-SRCs that elected to delay adoption in 2020, the Consolidated Appropriations Act (2021) (signed into law on December 27, 2020) further extended the permitted delay until 2022.

Upon adoption of CECL, banks are required to record a cumulative-effect "day-1" adjustment to credit loss allowances and retained earnings as of the beginning of the first reporting period in which CECL becomes effective. While this CECL day-1 impact is officially reported in the first Form 10-Q filed after CECL adoption (e.g., Q1 2020 10-Q for a calendar year-end non-SRC), entities provide information about the CECL day-1 impact earlier, as required by SEC Staff Accounting Bulletin No. 74 (SAB 74). SAB 74 requires entities to disclose a new standard's anticipated impact on the company's financial statements, i.e., the expected day-1 impact.⁹ The SEC paid special attention to enforcing SAB 74 disclosures relating to the CECL standard. For example, in 2018 SEC Chief Accountant Wes Bricker urged entities "to not let their implementation planning or disclosure of the anticipated effects of [CECL] lag during 2019".¹⁰

⁸ SRCs are companies that have (i) public float of less than \$250 million or (ii) annual revenues less than \$100 million and either no public float or public float less than \$700 million (<https://www.sec.gov/smallbusiness/goingpublic/SRC>).

⁹ <https://www.sec.gov/interps/account/sabcodet11.htm#M>

¹⁰ <https://www.sec.gov/news/speech/speech-bricker-121018-1>

2.2. Prior Literature on Credit Loss Recognition Timeliness and Expected Credit Losses

Prior literature on the timeliness of credit loss recognition primarily examines its effects on real actions, i.e., banks' lending and risk-taking decisions. This literature defines credit loss recognition timeliness as the extent to which credit loss provisions are positively related to future changes in nonperforming loans and/or future net charge-offs under the IL regime. Beatty and Liao (2011) find that banks with timelier credit loss recognition under the IL model are more willing to lend during recessionary periods. Using an international sample of banks, Bushman and Williams (2012) find that under the IL regime, timelier credit loss recognition that is not used to smooth earnings is associated with enhanced discipline over bank risk-taking. Bushman and Williams (2015) draw similar inferences based on U.S. banks and find that timelier credit loss recognition under the IL model is associated with lower individual bank risk and lower risk codependence among banks. Collectively, these studies propose that timelier credit loss recognition under the IL regimes has desirable effects on banks' lending and risk-taking, either through timelier regulatory capital constraints or by providing investors with information helpful in assessing (and thus disciplining) how efficiently and effectively banks have used their resources (FASB 2010a, para. OB4).

A more recent stream of literature examines the properties of researcher-constructed expected credit losses, which would be by nature timelier than incurred losses. These papers develop their own models to estimate expected credit losses using publicly available data. Covas and Nelson (2018) estimate expected losses using a vector autoregression methodology to forecast lifetime charge-off rates and conclude that CECL allowances would have been highly procyclical had CECL been in place during the 2007–2009 financial crisis. Harris et al. (2018) develop a measure of one-year-ahead expected rate of credit losses that outperforms net charge-offs in predicting one-year-ahead realized credit losses and contains incremental information about one-

year-ahead realized credit losses relative to the IL model. Lu and Nikolaev (2021) build on Harris et al. (2018) by developing a measure of expected long-term credit losses that subsumes information contained in the IL model with respect to predicting long-term losses. Wheeler (2021) develops a measure of lifetime expected credit losses using vintage analysis and finds that stock prices partially reflect his estimated expected loss information, even though it is not reflected in financial statements. Beatty and Liao (2021) examine analyst forecasts of loan loss provisions as a measure of informed market participants' expected credit loss estimates and find that analyst provision forecasts are incrementally predictive of future losses beyond IL provisions, especially for banks facing greater IL model constraints.

Our study builds upon these prior studies in two ways. First, relative to the literature on credit loss recognition timeliness, which is based on banks' discretionary timeliness variation under the IL model, CECL is an extreme form of timeliness. Lifetime expected credit loss estimates upon loan origination may not be sufficiently accurate to produce the benefits noted in prior research. Because CECL estimates are based on forecasted factors, and those forecasts could be highly related to existing factors, CECL has the potential to overstate lifetime expected losses during economic downturns and understate them during economic upturns. Second, relative to the literature on expected credit losses, our paper uses banks' own estimates of expected credit losses upon CECL adoption rather than researcher-constructed measures.¹¹ Analyzing banks' actual information allows us to extend prior literature by examining the extent to which CECL provides new information for investors.

¹¹ Banks' own estimates of expected losses could differ from researcher-constructed measures for several reasons. For example, banks' estimates may involve more discretion and bias than researchers' estimates, or researchers' estimates may rely on overly simplistic assumptions relative to the actual complexities facing banks. Thus, even with the findings of prior research, the properties of CECL allowances and their usefulness is an empirical question.

Recent studies examine the impact of IFRS 9 adoption, a standard issued by the IASB that also uses an expected credit losses approach. López-Espinosa et al. (2021) find that credit loss provision amounts under IFRS 9 are more predictive of future bank risk than IL provisions, especially in countries experiencing deterioration in credit conditions, with both the stock market and the CDS market reacting to disclosures of the day-1 impact of IFRS 9. Lejard, Paget-Blanc, and Casta (2021) find that the sovereign rating of a country is an important determinant of the day-1 impact of IFRS 9, and that the association between loan loss allowances and one-year-ahead charge-offs is not affected by IFRS 9 adoption while credit loss allowance information is less comparable across banks after IFRS 9 adoption.

While both CECL and IFRS 9 use expected credit losses, the standards differ on when and how expected credit losses are recognized. IFRS 9 categorizes financial assets into three “stages” based on their credit quality and applies different credit loss recognition criteria accordingly.¹² Specifically, for loans that represent most of a typical bank’s assets (i.e., stage-1 assets), IFRS 9 requires recognition of only the portion of lifetime credit losses expected within the next 12 months. By contrast, CECL requires recognition of total lifetime expected credit losses for all loans upon origination. Thus, CECL is even timelier credit loss recognition than IFRS 9, and it is unclear whether this extreme timeliness provides decision-useful information to investors.

3. Research Design, Sample Selection, and Descriptive Statistics

3.1. Research Design

3.1.1. Determinants of the CECL Day-1 Impact

We first examine the nature of CECL allowances, i.e., how banks determine the CECL day-1 impact to add to their IL allowances to comply with CECL, by estimating the cross-sectional

¹² Stage-1 assets include those with a low credit risk at the reporting date or without a significant increase in credit risk since initial recognition. Stage-2 assets include under-performing financial assets which exhibit a significant increase in credit risk since initial recognition. Stage-3 assets are those whose credit risk increases to a point where it is considered credit-impaired.

associations between bank characteristics and CECL allowances, IL allowances, and the CECL day-1 impact (i.e., “determinants”). This design uses banks that have adopted CECL and estimates determinants models as of the adoption date. The adoption date is the only date on which we can observe the IL allowance, the CECL allowance, and the CECL day-1 impact for the same bank at the same time. Thus, a benefit of this design is that differences in the determinants of IL and CECL allowances cannot be attributed to different banks or time periods.

We are interested in two groups of determinants. The first group includes determinants related to expected future credit losses. Relative to IL allowances, CECL allowances should reflect expected credit losses much further into the future (i.e., lifetime). Therefore, we expect CECL allowances to be more sensitive to indicators of loan riskiness than IL allowances. The second group of determinants includes those related to strategic bias. Prior research suggests that banks use discretion in the timing of credit loss recognition in the IL regime to smooth/manage earnings (Collins, Shackelford, and Wahlen 1995; Beatty, Ke, and Petroni 2002; Liu and Ryan 2006) or to manage regulatory capital (Moyer 1990; Collins, Shackelford, and Wahlen 1995; Beatty, Chamberlain, and Magliolo 1995; Kim and Kross 1998; Ahmed, Thomas, and Takeda 1999). Because CECL requires the recognition of lifetime expected losses without any recognition threshold or trigger events, CECL removes discretion on the timing of credit loss recognition and the subjectivity of judging whether losses are “probable,” which may lead to CECL allowances being less sensitive to strategic incentives than IL allowances. However, CECL potentially adds discretion related to bank managers’ reasonable and supportable forecasts of factors that affect loan collectability; entities can choose which factors to forecast, the optimism vs. pessimism of their forecasts, and the length of the reasonable and supportable period. Therefore, it is unclear whether CECL allowances are more or less sensitive to strategic incentives than IL allowances.

We estimate the following equation for CECL adopters on their adoption date using OLS:

$$\begin{aligned} \frac{Allowance_i}{Assets_i} = & \alpha_0 + \alpha_1 \frac{NPL_i}{Assets_i} + \alpha_2 \frac{Interest_i}{Assets_i} + \alpha_3 Smooth_i + \alpha_4 LowTier1_i + \alpha_5 \frac{RELoans_i}{Assets_i} \\ & + \alpha_6 \frac{ConsLoans_i}{Assets_i} + \alpha_7 \ln(Assets_i) + \varepsilon_i \end{aligned} \quad (1)$$

where subscript i indexes banks. The dependent variable, $\frac{Allowance}{Assets}$, is either the allowance for credit losses under the IL model ($IL_Allowance$), the CECL day-1 impact ($CECL_Impact$), or the allowance for credit losses under CECL ($CECL_Allowance$, which is equal to the sum of $IL_Allowance$ and $CECL_Impact$), all scaled by total assets as of the adoption date. To reflect the underlying riskiness of the loan portfolio, we include banks' nonperforming loans (NPL) scaled by total assets, and interest income on loans averaged over the previous 8 quarters ($Interest$) scaled by total assets. We predict positive associations between both variables and the dependent variables. $Smooth$ is the extent to which the bank recently smoothed earnings via credit loss provisioning, based on the "SmoothCoeff" measure in Narayanamoorthy and Wheeler (2021).¹³ We predict a positive association between $Smooth$ and allowance amounts because banks need larger allowances as "cookie jars" to smooth earnings in future periods. $LowTier1$ is an indicator set to one when the bank is weakly capitalized relative to its peers—specifically, when the bank's tier 1 risk-based capital ratio is in the lowest quintile among the sample banks. We predict a negative association with allowance amounts because banks with weaker capitalization have incentives to reduce their allowances to avoid violating regulatory capital requirements. To control for differences in bank size, business model, and loan composition, which may be related to IL and CECL allowance amounts, we include two variables capturing loan composition—real estate loans ($RELoans$) and consumer loans ($ConsLoans$), both scaled by total assets—and the natural

¹³ See the Appendix for more detail on the definition and construction of this and other variables.

log of bank total assets, $\ln(Assets)$. All variables are defined in detail in the Appendix. We winsorize all continuous variables at the 1st and 99th percentiles prior to estimating equation 1, and we cluster standard errors by bank to address heteroskedasticity.

3.1.2. The Usefulness of the CECL Day-1 Impact in Valuing Stocks

We next examine whether expected credit losses reported by banks upon CECL adoption are consistent with the information investors use when valuing banks. To do so, we examine the extent to which CECL and IL allowances explain contemporaneous equity prices, i.e., their “value relevance.” We estimate the following equation for CECL adopters on their adoption date using OLS:

$$Price_i = \alpha_0 + \alpha_1 \frac{CECL_Impact_i}{Shares_i} + \alpha_2 \frac{IL_Allowance_i}{Shares_i} + \alpha_3 \frac{BVE_Adjusted_i}{Shares_i} + \alpha_4 \frac{RELoans_i}{Shares_i} + \alpha_5 \frac{ConsLoans_i}{Shares_i} + \alpha_6 \frac{RateSensitive_i}{Shares_i} + \alpha_7 \frac{NIBP_i}{Shares_i} + \alpha_8 \frac{NPL_i}{Shares_i} + \varepsilon_i \quad (2)$$

where subscript i indexes banks. The dependent variable is stock price. We measure stock price at either fiscal year-end (i.e., one day prior to the CECL adoption date) or two quarters after the CECL adoption date (so the bank’s first Form 10-Q filing after CECL adoption is available to investors). *CECL_Impact* and *IL_Allowance* are as defined previously. *BVE_Adjusted* is the book value of equity before the IL allowance and is prior to any recognition of the CECL day-1 impact. We include several variables representing banks’ business model and loan composition, including *RELoans*, *ConsLoans*, rate-sensitive assets maturing within one year (*RateSensitive*), as well as net income before taxes and credit loss provisions (*NIBP*) and nonperforming loans (*NPL*), which reflect overall financial performance and information about underlying loan quality that is available to investors both before and after CECL. Following Barth and Clinch (2009), we deflate all variables by common shares outstanding (*Shares*). All variables are defined in detail in the

Appendix. We winsorize all continuous variables at the 1st and 99th percentiles prior to estimating equation 2, and we cluster standard errors by bank to address heteroskedasticity.

Consistent with prior research (e.g., McInnis, Yu, and Yust 2018; Barth, Li, and McClure 2021), we measure value relevance based on the explanatory power of accounting information for equity values. Our interest in equation 2 is whether including *CECL_Impact* significantly improves explanatory power relative to a version of equation 2 that excludes *CECL_Impact*. This design implicitly compares the CECL and IL regimes for the same banks at the same time. A significantly negative coefficient on *CECL_Impact* is consistent with investors assessing equity value to be lower when the incremental credit losses recognized upon day-1 CECL adoption are higher. Such a finding implies that CECL significantly improves the value relevance of allowance information incrementally to the IL model.

3.1.3. The Usefulness of the CECL Day-1 Impact in Predicting Future Credit Losses

Next, we examine whether CECL improves the ability to predict future credit losses. CECL was intended to improve upon the IL model by recognizing expected credit losses in a timelier manner, which should make CECL allowances more predictive of future credit losses than IL allowances. Prior research examines how credit loss reserves in the IL regime predict future credit losses by examining the behavior of banks' quarterly or annual loan loss provision (Beatty and Liao 2011, 2014; Bushman and Williams 2012, 2015; Nicoletti 2018). We deviate from this design because CECL and IL provisions are not observable contemporaneously: after adopting CECL, banks do not disclose the IL allowances or provisions, and prior to adopting CECL, banks do not disclose the CECL allowances or provisions. Contemporaneous accounting numbers under both the CECL and IL models are available only on the date of adoption, when banks report both the IL allowances and the CECL day-1 impact on allowances. Thus, we examine the extent to which CECL and IL allowances on the adoption date predict future credit losses. Following prior studies,

we use two proxies for future credit losses: future nonperforming loans (Beatty and Liao 2021) and future net charge-offs (Harris et al. 2018; Wheeler 2021). We estimate the following equation for CECL adopters using OLS:

$$\begin{aligned} \frac{CreditLosses_i}{Assets_i} = & \alpha_0 + \alpha_1 \frac{CECL_Impact_i}{Assets_i} + \alpha_2 \frac{IL_Allowance_i}{Assets_i} + \alpha_3 \frac{RELoans_i}{Assets_i} + \alpha_4 \frac{ConsLoans_i}{Assets_i} \\ & + \alpha_5 \frac{RateSensitive_i}{Assets_i} + \alpha_6 \frac{NIBP_i}{Assets_i} + \varepsilon_i \end{aligned} \quad (3)$$

where subscript i indexes banks. The dependent variable is either one- or four-quarter-ahead nonperforming loans (NPL_{t+1} and NPL_{t+4} , respectively) scaled by total assets, one-quarter-ahead net charge-offs (NCO_{t+1}) scaled by total assets, or net charge-offs scaled by total assets cumulated over the next four quarters ($\sum(\frac{NCO}{Assets})_{t+1:4}$). All other variables are as previously defined. We winsorize all continuous variables at the 1st and 99th percentiles prior to estimating equation 3, and we cluster standard errors by bank to address heteroskedasticity.

Similar to our value relevance tests, our interest in equation 3 is whether including *CECL_Impact* significantly improves explanatory power relative to a version of equation 3 that excludes *CECL_Impact*. Similar to our value relevance tests, this design implicitly compares the CECL and IL credit loss regimes for the same banks at the same time. A significantly positive coefficient on *CECL_Impact* implies that CECL significantly improves the predictability of future credit losses incrementally to the IL model.

3.1.4. Are CECL Expected Credit Losses New Information for Investors?

Next, we address whether CECL information is new to investors, or whether it merely confirms their expectations (consistent with investors incorporating expected loan loss information prior to CECL, e.g., Wheeler 2021).¹⁴ We take two approaches to explore this question. First, we

¹⁴ Information that merely confirms expectations is still relevant for investors. The FASB's Conceptual Framework defines relevant information as having predictive value, confirmatory value, or both (FASB 2010b, para. QC6-10).

examine investor response to banks' CECL SAB 74 estimates leading up to adoption. Second, we use the Covid-19 pandemic to examine whether information about CECL day-1 impacts mitigates investor uncertainty when uncertainty about future credit losses increases unexpectedly.

To examine investor response to estimates of CECL impact, we hand-collect information from banks' SAB 74 disclosures related to CECL. As discussed previously, the SEC requires companies to disclose the potential effects of "accounting standards which have been issued but not yet adopted by the registrant unless the impact on its financial position and results of operations is not expected to be material."¹⁵ A well-specified test of investor response to such information would require a measure of investors' expectations of CECL day-1 impacts, as investors should only respond to unexpected CECL impacts. While we do not have investor expectations for the initial CECL estimate, we use initial disclosures as a baseline, with revisions to such estimates reflecting potentially new information to investors.

We use an event study design around banks' quarterly earnings announcement/filing cycle. Specifically, using the following regression model, we examine how revisions to the banks' CECL estimates are associated with investor response (i.e., abnormal stock returns), beginning on the day of the earnings announcement through one day after the bank's 10-K/Q filing¹⁶ –

$$Return[EA\ day\ 0\ to\ 10-K/Q+1]_{i,t} = \alpha_0 + \alpha_1 \Delta CECL\ SAB\ 74\ Estimate/MVE + \sum \alpha_k Controls_{i,t} + \sum \alpha_n FE_t + \varepsilon_{i,t} \quad (4)$$

Where $\Delta CECL\ SAB\ 74\ Estimate$ is the change in the firm's estimate of the impact of CECL, beginning with Q1 2019 through Q1 2020 (with the final quarter's change calculated using the actual recognized CECL day-1 impact). The vector *Controls* includes control variables intended

¹⁵ <https://www.sec.gov/interps/account/sabcodet11.htm#M>

¹⁶ We use this event window because our hand collection approach focuses on the quarterly and annual filings (10-Q and 10-K, respectively), but it is possible that SAB 74 estimates disclosed in those filings were discussed or disclosed in the precursor quarterly earnings announcement or conference call, so we include those events in the return window. The abnormal return is calculated by subtracting the market value-weighted daily return from the bank's daily return.

to capture the firms general liquidity and information environment, the impact of unexpected earnings for that quarterly reporting cycle, and properties of the CECL estimate. Specifically, to control for factors related to information environment and liquidity, we include the natural log of one plus the number of analysts following the firm ($\ln(1+Analysts)$), the natural log of the market value of equity ($\ln(MVE)$), the book value of equity divided by the market value of equity (*Book-to-Market*), and the cumulative bank stock return leading up to the announcement, starting 50 trading days prior to the announcement until five days prior to the announcement (*Pre-EA Return*). To control for the impact of unexpected earnings around the announcement and filing window, we control for the analyst forecast error, scaled by price (*UE*). To control for properties of the estimate, we include an indicator for whether the estimate is a point forecast (*Point*), which takes a value of zero for a range forecast (in which case we take the mean of the high and low ends of the range for purposes of constructing the *CECL SAB 74 Estimate*).

Second, we test whether information about CECL day-1 impacts mitigates investor uncertainty when uncertainty about future credit losses increases unexpectedly. We use the onset of the COVID-19 pandemic in late February 2020 as an exogenous shock that substantially increased both the level and uncertainty of expected credit losses. We expect that this increase in uncertainty is lower to the extent that investors are better informed about expected credit losses. While investors can estimate expected credit losses for banks regardless of CECL adoption (Wheeler 2021), banks adopting CECL are required to provide expected CECL day-1 impacts to comply with SAB 74. If information about CECL day-1 impacts is new, i.e., not available to investors absent such disclosures, then investors' ability to estimate credit losses should be superior when banks have provided expected CECL day-1 impacts, as compared to when banks

have not provided this information. Therefore, we test whether the increase in uncertainty at the onset of the COVID crisis is less severe for banks disclosing expected CECL day-1 impacts.

We use a difference-in-differences design, with February 21, 2020 – March 24, 2020 as our “treatment” period. This period marks the onset of the COVID-19 crisis in the U.S and is characterized by a rapid, substantial increase in the CBOE Volatility Index (VIX), a commonly used barometer of market uncertainty (see Figure 1A). Our “treatment” period ends prior to the passage of the CARES Act, i.e., prior to non-SRC banks receiving an option to delay CECL implementation. We use January 1, 2020 – February 20, 2020 as the “control” period, as it predated the widespread emergence of COVID-19 in the U.S. and is characterized by lower, more stable VIX, and hence lower uncertainty regarding expected credit losses (see Figure 1A).

Our “treatment” and “control” banks are defined based on whether the bank was required to adopt CECL prior to the onset of the COVID crisis, and therefore subject to SAB 74 disclosure requirements about expected CECL day-1 impacts. Our “treatment” banks are calendar year-end non-SRC banks, which, as of the end of our treatment period, were required to adopt CECL on January 1, 2020.¹⁷ Our “control” banks are calendar year-end SRC banks. These banks were not required to adopt CECL until January 1, 2023, and SAB 74 requirements about the expected CECL day-1 impact would not apply to these banks before the onset of the COVID crisis in 2020.¹⁸

We estimate the following equation for banks with the necessary data using OLS:

$$\begin{aligned} MarketMeasure_{i,t} = & \alpha_0 + \alpha_1 CECL_i \times Post_t + \sum \alpha_k Controls_{i,t} + \sum \alpha_n Controls_{i,t} \times Post_t \\ & + \sum \alpha_m FE_i + \sum \alpha_p FE_t + \varepsilon_{i,t} \end{aligned} \quad (5)$$

¹⁷ Non-SRC banks that ultimately ended up delaying CECL adoption under the CARES Act were subject to SAB 74 disclosure requirements prior to the onset of COVID and are therefore still considered “treatment” banks. Using the hand-collected data discussed above for the SAB 74 investor response test, we drop treatment banks that did not have a CECL SAB 74 disclosure until 2020 (as further detailed in Table 1 and Section 4.X).

¹⁸ Companies classified as Emerging Growth Companies (EGC) are permitted to delay adoption of CECL until they lose their EGC status (<https://www.sec.gov/smallbusiness/goingpublic/EGC>). We classify non-SRC EGCs that we identify as having delayed CECL adoption as “control” banks because they would likely not have provided SAB 74 disclosures prior to the onset of the COVID crisis.

where subscripts i and t index bank and trading day, respectively. The dependent variable, *MarketMeasure*, is a measure of either information asymmetry or stock liquidity. Following prior studies (e.g., Blankespoor, Miller, and White 2014; Nagar, Schoenfeld, and Wellman 2019), we use percent quoted bid-ask spread based on Daily Trade and Quote (DTAQ) data to proxy for information asymmetry (*Spread*), as percent quoted bid-ask spread is a widely used spread benchmark measure (see, e.g., Goyenko, Holden, and Trzcinka 2009; Fong, Holden, and Trzcinka 2017). Our proxy for stock liquidity is the daily price impact based on DTAQ data (*PriceImpact*). *CECL* is an indicator variable equal to 1 (0) for our “treatment” (“control”) banks. *Post* is an indicator variable equal to 1 (0) for days during our “treatment” (“control”) period. The variable of interest is the interaction term $CECL \times Post$. $\alpha_1 < 0$ indicates that banks providing CECL information prior to the onset of COVID experienced a significantly smaller increase in investor uncertainty. Such a finding would be consistent with CECL providing new information that helps mitigate investors’ uncertainty about expected credit losses.

The vector *Controls* includes several sets of control variables following prior literature (e.g., Christensen, Hail, and Leuz 2013; Hail, Muhn, and Oesch 2021). We include the following contemporaneous (i.e., daily) variables: stock return (*Return*), the natural logarithm of market capitalization ($\ln(MVE)$), share turnover (*Turnover*), and quote-based stock volatility based on DTAQ data (*StockVol*). Since the relation between the dependent variables and bank size could be nonlinear, we additionally control for the square and cubic forms of $\ln(MVE)$: $\ln(MVE)^2$ and $\ln(MVE)^3$, respectively. In addition, we control for the following quarterly factors, measuring them as of the most recently available quarterly data for bank i as of day t : (i) capital adequacy, proxied by the tier-1 capital ratio (*Tier1Ratio*); (ii) loan riskiness, proxied by $\frac{NPL}{Assets}$ and $\frac{Interest}{Assets}$; (iii) profitability, proxied by net income divided by total assets ($\frac{NetIncome}{Assets}$); and (iv) loan portfolio

composition ($\frac{RELoans}{Assets}$ and $\frac{ConsLoans}{Assets}$). We include two indicator variables (*CCAR2020* and *PriorStressTest*) as controls for possible effects of stress tests on banks’ information asymmetry and stock liquidity. As controls for possible effects of earnings announcements or 10-K filings on banks’ information asymmetry and stock liquidity, we include indicators for trading days on or after a bank’s Q4 2019 earnings announcement (*EA*) and 10-K filing (*10KFiled*). To account for the possibility that the relation between the control variables and market measures may differ after the onset of COVID, we include in equation 4 the interaction between *Post* and each variable in the vector *Controls*. Finally, we include bank and trading-day fixed effects to account for bank- or time-invariant differences, respectively, in our independent or dependent variables. We winsorize all continuous variables at the 1st and 99th percentiles and we cluster standard errors by bank and trading day.

3.2. Sample Selection, Descriptive statistics

3.2.1 Sample Selection

Table 1 presents a summary of the sample selection procedure. We begin with all publicly traded U.S. banks (identified using SIC codes 6000 – 6299) available on S&P Capital IQ Pro (“SPCIQ,” formerly SNL Financial) with a credit loss allowance balance, coverage in CRSP, and the necessary bank-level variables from the “Companies” dataset in SPCIQ.¹⁹

For the analyses on the determinants and decision-usefulness of the CECL day-1 impact (as described in Sections 3.1.1 through 3.1.3), we classify banks with non-missing CECL day-1 impacts (*CECL_Impact*) in SPCIQ as CECL adopters.²⁰ In instances where reported CECL day-1

¹⁹ Day-1 impact variables are obtained from the “Regulated Depositories (U.S.)” dataset in SPCIQ.

²⁰ Our data source for *CECL_Impact* potentially understates the full impact of CECL on credit loss allowances for some banks because it excludes allowances on unfunded loan commitments, which are recognized for the first time upon CECL adoption. A potential alternative measure of the CECL day-1 impact is the effect of day-1 CECL adoption on retained earnings, which includes the allowance on unfunded loan commitments. However, this amount excludes effects related to PCD assets (as explained in Section 2.1), and its net-of-tax amount is less comparable to

impacts in SPCIQ are 0, we hand-collect day-1 impact data from regulatory filings (i.e., FR Y-9C reports and call reports) and SEC filings (i.e., 10-Qs) to confirm banks' adoption of CECL and day-1 impact amounts. We also hand-collect day-1 impact data for non-SRCs (i.e., banks required to adopt CECL) with missing CECL day-1 impacts in SPCIQ, because it is unclear whether these banks have adopted CECL or delayed adoption. Our final sample for CECL day-1 impact analyses consists of 197 publicly traded banks that adopted CECL during January 1, 2020 – January 1, 2021.²¹

For the SAB 74 investor response analyses, we begin by hand-collecting SAB 74 CECL estimates for the 197 CECL-adopting banks described above. We drop 34 banks that did not have at least two quarters of interpretable CECL estimates (two quarters are required to first establish a baseline for a subsequent revision to investor expectations). We then drop 5 banks with missing data for the variables required in the regression, leaving 158 banks, from which we have 244 quarterly observations.

For the COVID analyses on whether CECL provides new information to investors (as described in Section 3.1.4), we require intraday data on bid-ask spread and price impact available in the “Millisecond Intraday Indicators by WRDS” dataset from WRDS. To identify banks' SRC status, we use the SEC's criteria for SRC status and approximate public float using our market value of equity variable from CRSP (*MVE*). To mitigate errors, we hand collect SRC status from the 10-K/Q filing for Q4 2019 for the subset of banks where our approximation had the highest potential for misclassification. We also drop non-SRC banks with non-calendar fiscal year-ends

IL Allowance. We find similar inferences to those in Tables 3, 4, and 5 using this alternative measure in place of *CECL_Impact* (untabulated).

²¹ 159 of these banks have a calendar year-end, and thus adopted on January 1, 2020, while 9 have a non-calendar year-end, and thus adopted later in 2020. The remaining 29 banks adopted CECL on January 1, 2021, with 12 retrospectively applying CECL as of January 1, 2020 and 17 applying it as of January 1, 2021.

because these banks' scheduled adoption date was after January 1, 2020, and it is unclear whether they would have provided estimates of the CECL day-1 impact prior to our "treatment" period; thus, classifying them as "treatment" or "control" banks is ambiguous. Finally, we drop all banks that do not have a SAB 74 disclosure that estimates the potential impact of CECL prior to 2020, as an important assumption for the COVID analysis is that investors had information about the potential impact of CECL for treatment banks prior to the onset of the pandemic. The final sample for the COVID analyses consists of 11,378 daily observations – 6,726 in the "control" period and 4,652 in the "treatment" period – from 65 "treatment" banks and 142 "control" banks.

3.2.2 Descriptive statistics

The descriptive statistics for variables used in the CECL day-1 impact analyses are presented in Panel A, Table 2. The average CECL day-1 impact on credit loss reserves is approximately 0.2% of total assets ($\frac{CECL_Impact}{Assets}$); for comparison, the average allowance for loan and lease losses under the IL model is approximately 0.7% of total assets ($\frac{IL_Allowance}{Assets}$). Thus, for the average bank, day-1 adoption of CECL increases its credit loss allowance amount by 30%. For approximately 10% of the 197 sample banks, the CECL day-1 impact on allowances was negative, indicating that CECL adoption resulted in a *decline* in credit loss reserves.

The descriptive statistics for variables used in the SAB 74 investor response analysis are presented in Panel B, Table 2. The descriptives indicate that there were revisions that increased and decreased CECL estimates, with the median change being zero, and the standard deviation being 0.48% of a firm's market value of equity. The mean of *Pre-EA Return* is -0.223, influenced significantly by the large decline in bank valuations during the latter part of Q1 2020.

The descriptive statistics for variables used in the COVID analyses are presented in Panel B, Table 2, separately for the treatment banks and the control banks during both periods. The

sample includes 6,086 (4,550) daily observations from the treatment (control) banks in the control period, and 4,117 (3,180) daily observations from the treatment (control) banks in the treatment period. The average daily quoted bid-ask spread is 0.001 (0.019) for the treatment (control) banks in the control period, and 0.003 (0.043) for the treatment (control) banks in the treatment period, suggesting a substantial increase in bid-ask spread from the control period to the treatment period for both groups of banks. The average daily price impact is 0.001 (0.005) for the treatment (control) banks in the control period, and 0.002 (0.012) for the treatment (control) banks in the treatment period, suggesting a substantial increase in price impact (i.e., decrease in stock liquidity) from the control period to the treatment period for both groups of banks. Consistent with the SRC classification by the SEC being based on public floats and revenue, the average market value of equity is substantially larger for the average non-SRC bank than the average SRC banks—approximately \$28,529 million (\$209 million) for the treatment (control) banks in the control period, and \$21,980 million (\$170 million) for the treatment (control) banks in the treatment period.

4. Results

4.1. Determinants of the CECL Day-1 Impact

Table 3 presents the results of estimating equation 1 for IL allowances (column 1), the CECL day-1 impact (column 2), and the overall CECL allowance ($IL_Allowance + CECL_Impact$, column 3). Results in column 1 indicate that IL allowances are positively related to loan riskiness, based on the significantly positive associations of allowances with nonperforming loans ($\frac{NPL}{Assets}$) and interest income on loans ($\frac{Interest}{Assets}$). We find no evidence that IL allowances are higher when banks have a history of more aggressively smoothing earnings via credit loss provisioning ($Smooth$), and no evidence that IL allowances depend on whether banks have low regulatory capital ratios relative to peers ($LowTier1$).

Column 2 presents the determinants of the CECL day-1 impact, i.e., the amount banks add to their allowances to comply with CECL. Results in column 2 indicate that banks have larger CECL day-1 impacts when there is a larger amount of nonperforming loans ($\frac{NPL}{Assets}$) and when interest income from loans ($\frac{Interest}{Assets}$) is higher, which indicates that the CECL day-1 impact is positively related to loan riskiness. We find a marginally significant negative coefficient on *Smooth*, which indicates that CECL day-1 impacts potentially correct for discretion in IL allowances that could be used to smooth earnings. We find no evidence that the CECL day-1 impact depends on whether banks have low regulatory capital ratios relative to peers (*LowTier1*). We also find a significantly positive coefficient on $\frac{ConsLoans}{Assets}$, which is consistent with the CECL day-1 impact being primarily related to credit card debt. Overall, the CECL day-1 impact reflects loan riskiness and is not associated (or is even weakly negatively associated) with strategic incentives.

Column 3 presents determinants of CECL allowances, which yield similar inferences to the results in column 2. In untabulated tests, we compare the coefficients from columns 1 and 3 on our four variables of interest, to test the overall differences between IL and CECL allowances. The coefficients on $\frac{NPL}{Assets}$ and $\frac{Interest}{Assets}$ are significantly different between columns 1 and 3 at the 5% level, and the coefficients on *Smooth* are significantly different at the 10% level. These findings suggest that CECL allowances are more strongly related to loan riskiness, and somewhat *less* strongly related to strategic incentives, than IL allowances.

4.2. The Usefulness of the CECL Day-1 Impact in Valuing Stocks

Table 4 presents the results of estimating equation 2. Columns 1–3 examine the extent to which accounting information explains contemporaneous prices, potentially prior to the precise accounting information being revealed to investors. Columns 4–6 examine the extent to which

accounting information explains prices after the precise accounting information has been revealed to investors. For benchmarking purposes, columns 1 and 4 present value relevance without any allowance information. Columns 2 and 5 add the IL allowance ($\frac{IL_Allowance}{Shares}$). As predicted, the coefficient on the IL allowance is significantly negative, consistent with investors reducing valuation when incurred credit losses are higher. Columns 3 and 6 add the CECL day-1 impact ($\frac{CECL_Impact}{Shares}$), and we find a significantly negative coefficient, as predicted, consistent with investors reducing valuation when expected credit losses are higher. This is consistent with the findings of prior research (e.g., Wheeler 2021) that investors incorporate expected credit losses into stock pricing.²² Given that the models in columns 2 and 3 (5 and 6) are nested, the significant coefficient also indicates that the explanatory power of the model with the incremental allowance for lifetime credit losses (e.g., 0.924 in column 3) is significantly higher than that of the model without the incremental allowance (e.g., 0.902 in column 2). This finding is consistent with CECL providing more value-relevant information about credit losses to investors than accounting under the IL model.

4.3. *The Usefulness of the CECL Day-1 Impact in Predicting Future Credit Losses*

Table 5 presents the results of estimating equation 3. Panel A (Panel B) reports results when we measure future credit losses using reported future nonperforming loans (net charge-offs). In both panels, columns 1-3 present results related to credit losses one quarter ahead and columns

²² Relative to Wheeler (2021; see Table 5, column 1 on p. 39), we document an association between price and the incremental allowance for lifetime credit losses (i.e., CECL day-1 impact) that is much more negative (−12.021 vs. −0.744). One possible explanation is that potential measurement errors in researcher-constructed expected loss measures bias coefficients towards zero. Another explanation is that investors' pricing of expected credit differs in 2019-2020 (i.e., our sample period) relative to 2006-2016 (i.e., the sample period in Wheeler (2021)). For example, banks in our sample period provide estimates of CECL day-1 impacts to investors due to SAB 74 requirements, while banks during the sample period in Wheeler (2021) did not, and information availability could increase the pricing of expected credit losses. The association between price and the IL allowance that we document is also more negative than that in Wheeler (2021) (−5.720 vs. −3.016), but this is explained by our removing the allowance from book value of equity and the provision for loan losses from net income. Wheeler (2021) does not adjust book value of equity or net income, so the IL allowance information is reflected in three variables rather than one.

4-6 present results related to credit losses four quarters ahead. In Panel A, we find that the IL allowance significantly improves the predictability of future credit losses both one quarter ahead (adjusted r-squared of 0.176 in column 2 compared to 0.073 in column 1) and four quarters ahead (adjusted r-squared of 0.134 in column 5 compared to 0.022 in column 4). We also find that the CECL day-1 impact significantly improves the predictability of future credit losses incrementally to the IL allowance, both one quarter ahead (adjusted r-squared of 0.307 in column 3 compared to 0.176 in column 2) and four quarters ahead (adjusted r-squared of 0.227 in column 6 compared to 0.134 in column 5). This finding is consistent with CECL information being incrementally useful for investors because it improves the predictability of future credit losses. In Panel B, we find similar inferences when measuring future credit losses using future net charge-offs. Specifically, the CECL day-1 impact significantly increases the predictive power of the accounting information for both one-quarter-ahead net charge-offs (adjusted r-squared of 0.691 in column 3 compared to 0.631 in column 2), and cumulative net charge-offs over future four quarters (adjusted r-squared of 0.782 in column 6 compared to 0.734 in column 5).

Together, the results in Tables 3, 4, and 5 suggest that relative to the IL model, CECL provides better information about potential future loan losses and is more consistent with the information investors find relevant when setting prices. These findings suggest that the recognition and measurement of credit losses under CECL “provid[es] financial statement users with more decision-useful information about the expected credit losses on financial instruments” (FASB 2016).

4.4. Are CECL Expected Credit Losses New Information for Investors?

4.4.1 Investor Response to SAB 74 Estimates

The SAB 74 disclosures that we hand collected help provide baseline CECL estimates, which allows for a measure of unexpected CECL impacts (i.e., revisions in CECL estimates). If

investors respond to these unexpected impacts, this provides evidence that the standard provided new information to investors about loan quality and future loan performance. Columns 1 and 2 of Table 6 report the OLS estimation of equation 4, with $Return[EA \text{ day } 0 \text{ to } 10\text{-}K/Q+1]$ as the dependent variable, measured as a buy-and-hold abnormal return (column 1) and a cumulative abnormal return (column 2).²³ Consistent with revisions in the CECL estimated impacts reflecting new information to investors, the coefficient on $\Delta CECL \text{ SAB } 74 \text{ Estimate}$ is negative and significant, which suggests that investors perceive an increase (decrease) in the CECL SAB 74 estimate as bad (good) news. Overall, the results in Table 6 are consistent with CECL estimates providing information not available under the IL regime.

4.4.2 Investor response to uncertainty related to COVID

Columns 1 and 2 (3 and 4) of Panel B, Table 7 reports the OLS estimation of equation 4 with $Spread (PriceImpact)$ as the dependent variable. Columns 1 and 3 include only the interaction term of interest — $CECL \times Post$ — and bank and trading day fixed effects. In both columns, the coefficient on $CECL \times Post$ is significantly negative, which suggests that banks providing expected credit loss information experience a smaller increase in bid-ask spread and a smaller increase in price impact (i.e., a smaller increase in stock illiquidity) during the onset of COVID. These findings continue to hold after including controls and interactions (columns 2 and 4), though the magnitudes of the coefficients on $CECL \times Post$ are smaller. Overall, the results in Table 7 are consistent with CECL providing information not available under the IL regime and reducing investor uncertainty about potential future losses.²⁴

²³ We use different approaches to cumulating the return because the return window varies for each bank-quarter observation, depending on the time lag between the earnings announcement and the 10-K/Q filing, with the average time lag being 18.5 calendar days.

²⁴ Our results on bid-ask spread are robust to using the natural log transformation of one plus percent quoted bid-ask spread based on DTAQ data, the percent effective bid-ask spread based on DTAQ data (which reflects spread of trades that occur inside the quoted spread), and the daily closing bid-ask spread from CRSP. Our results on price impact are robust to using the natural log transformation of one plus price impact.

5. Additional Analyses and Robustness Tests

5.1. Alternative Specifications Comparing CECL and IL Allowances

Our tests of the incremental value relevance and predictive ability of CECL in Tables 4 and 5 focus on whether the CECL day-1 impact has incremental explanatory power over the IL allowance. In this section, we compare IL and CECL allowances' relative information content (Biddle, Seow, and Siegel 1995; McInnis et al. 2018), which is more consistent with the choice the FASB made in issuing ASU 2016-13 and replacing (i.e., prohibiting the use of) the IL model.

To compare relative information content, we estimate two versions of equations 2 and 3 for our value relevance and predictive ability tests, respectively. The first version of both equations contains *IL_Allowance* (but not *CECL_Impact*), and the second contains *CECL_Allowance* (which equals *IL_Allowance* + *CECL_Impact*). We compare the explanatory power of the two non-nested models using the Clarke (2003, 2007) test.²⁵

Table 8 reports the results of this analysis for our value relevance tests. Comparing columns 1 and 2 reveals that CECL allowances explain equity values better than IL allowances for a significant majority of banks; 151 of 197 banks (about 77 percent) have lower unexplained variation using CECL allowances (Clarke test p-value < 0.01, untabulated). Comparing columns 3 and 4 reveals similar findings; 153 of 194 banks (about 79 percent) have lower unexplained variation using CECL allowances (Clarke test p-value < 0.01, untabulated).

Table 9 reports the results of this analysis for our tests of predicting future credit losses. Panel A presents results using future nonperforming loans and Panel B presents results using future net charge-offs. In panel A, comparing columns 1 and 2 reveals that CECL allowances predict

²⁵ Given two non-nested models, the Clarke test determines whether a significantly greater number of observations have lower unexplained variation based on one model or the other. Clarke (2007) finds that this nonparametric test is more powerful in choosing the model with better explanatory power than the Vuong (1989) test, and the Clarke test has been used in recent accounting research (e.g., Barth, Gow, and Taylor 2012; Campbell, Gee, and Wiebe 2021).

future credit losses better than IL allowances for a significant majority of banks; 150 of 197 banks (about 76 percent) have lower unexplained variation using CECL allowances (Clarke test p-value < 0.01 , untabulated). Comparing columns 3 and 4 in Panel A reveals similar findings; 108 of 155 banks (about 70 percent) have lower unexplained variation using CECL allowances (Clarke test p-value < 0.01 , untabulated). Panel B provides identical inferences, with approximately 76 percent of banks having lower unexplained variation using CECL allowances (Clarke test p-values < 0.01 , untabulated). Overall, the results in Tables 8 and 9 indicate that CECL allowances provide greater relative information content than IL allowances.

5.2. Robustness Tests related to the COVID Analyses

5.2.1. Placebo tests

A concern with comparing non-SRC and SRC banks as treatment and control banks is that treatment banks are larger than control banks, and findings may be attributable to size differences rather than information about CECL day-1 impacts. While we already include polynomials of logged market value as controls to mitigate this concern, we secondarily mitigate the concern via placebo tests around a similar spike in investor uncertainty during the financial crisis (which preceded CECL).

We conduct placebo tests using the period of September 15 – October 17, 2008 as the placebo treatment period, which exhibits a similarly rapid, substantial increase in VIX as the treatment period of our main analyses (see Figure 1B). The placebo control period is July 26 – September 14, 2008, which is characterized by lower, more stable VIX, as shown in Figure 1B. The lengths of the placebo treatment and control periods are identical to those of the treatment and control periods in our main analyses. We conduct the placebo test using two approaches for identifying non-SRC (i.e., treatment) and SRC (i.e., control) banks during the placebo period. First, we retain banks' SRC classification from our sample period and use this same classification during

the placebo period; Panel A of Table 10 presents the results of the placebo test using this “retain classification approach”. Second, we reclassify banks as SRC and non-SRC during the placebo period using the SEC’s classification during that period;²⁶ Panel B of Table 10 presents the results of the placebo test using this “reclassify approach”. In both panels, none of the coefficients on $CECL \times Post_Placebo$ are statistically different from zero. Based on these findings, we conclude that the treatment banks and the control banks exhibit no evidence of differentially lower information asymmetry or stock illiquidity during a crisis period before the adoption of CECL.

5.2.2. Examination of Pre-Treatment Period Trends

Our difference-in-differences design relies on an assumption of parallel trends, i.e., that differences in bid-ask spread and stock illiquidity between the control and treatment banks would have remained unchanged during the onset of COVID had the treatment banks not provided information about the expected CECL day-1 impact. While the parallel trends assumption is not directly testable, we examine trends in bid-ask spreads and stock illiquidity prior to the onset of COVID to determine whether evidence exists that casts doubt on the parallel trends assumption.

We first expand the control period to range from September 1, 2019 to February 20, 2020, and replicate our main analyses. Table 10, Panel C, reports the results of these tests; our inferences are identical to our main analyses reported in Table 7. Next, we examine the time trend in bid-ask spread and price impact during the last three months of the control period, from December 1, 2019, to February 20, 2020, using indicator variables for each of these three months, *Dec2019*, *Jan2020*, and *Feb2020*. Table 10, Panel D, presents the results of this test. Out of the six interaction terms of interest across columns 1–2, only $CECL \times Feb2020$ in column 1 has a statistically significant coefficient (coefficient = -0.002, t-value = -1.79). The magnitude of the coefficient, however, is

²⁶ In 2018, the SEC raised the thresholds in the SRC definition, as defined in Item 10(f)(1) of Regulation S-K (see <https://www.sec.gov/corpfin/amendments-smaller-reporting-company-definition>). Thus, a bank that qualifies as an SRC in our treatment period (i.e., 2020) may not qualify as an SRC in 2008.

less than one-third of the coefficient of -0.007 on $CECL \times Post$ in our main analysis reported in column 2 of Table 7. Thus, overall, we find little evidence that is inconsistent with the parallel trends assumption.

6. Conclusion

We examine the decision-usefulness of expected credit loss information provided by banks adopting CECL. The FASB issued ASU 2016-13 in June 2016 to provide more decision-useful information to users of financial statements than was available under the IL model. To our knowledge, we provide the first empirical evidence on the impact of CECL implementation on banks' credit loss reserves and whether this information is useful to equity investors. Our empirical evidence suggests that CECL credit loss allowances are more useful in valuing stocks and are better predictors of future credit losses than those under the IL regime. Importantly, we also find that banks' own estimates of CECL credit losses provide investors with new information, which has not been shown in prior research. We contribute to existing research on timelier credit loss recognition, including the research examining the properties of researcher-constructed expected credit losses. We study exclusively CECL adoption, which allows us to compare contemporaneous IL and CECL allowances for many of our analyses. Future research could examine the properties of CECL provisions and compare those findings to the literature on credit loss provisions under the IL model.

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Appendix: Variable Definitions²⁷

Variable	Definition
<i>10KFiled</i>	Daily indicator equal to 1 for trading days on or after the bank’s 10-K filing for 2019, and 0 otherwise.
<i>Analysts</i>	The number of analysts contributing to the I/B/E/S consensus street forecast that is used in calculating unexpected earnings (<i>UE</i>).
<i>Assets</i>	Total assets (SPCIQ Keyfield 280297).
<i>Book-to-Market</i>	Book value of equity scaled by market value of equity.
<i>BVE_Adjusted</i>	Book value of equity excluding minority interest (SPCIQ Keyfield 280318) plus the allowance for loan and lease losses under the incurred loss model (SPCIQ Keyfield 280287).
<i>CCAR2020</i>	An indicator variable equal to 1 if the bank participated in the 2020 Comprehensive Capital Analysis and Review (CCAR) stress test, and 0 otherwise.
<i>ΔCECL SAB 74 Estimate</i>	Change in the firm’s estimate of the impact of CECL, calculated as the CECL SAB 74 estimate for quarter t minus the most recently disclosed CECL SAB 74 estimate.
<i>CECL</i>	An indicator variable for the COVID analyses, equal to 1 for our “treatment” banks (which are calendar-year-end non-SRC banks), and 0 for our “control” banks (which are calendar-year-end SRC banks).
<i>CECL_Allowance</i>	Total credit loss allowances under CECL on day-1 of CECL adoption. This is calculated as the allowance for loan and lease losses under the incurred loss model (SPCIQ Keyfield 280287), plus the effect of CECL adoption on allowances for credit losses on loans and leases held for investment and held-to-maturity debt securities (SNL Keyfield 319096).
<i>CECL_Impact</i>	The effect of day-one CECL adoption on allowances for credit losses on loans and leases held for investment and held-to-maturity debt securities (SNL Keyfield 319096), including the initial allowance gross-up for any purchased credit-deteriorated assets held as of the adoption date.
<i>CECL_p</i>	An indicator variable for the treatment vs control banks for the placebo test of the COVID analyses using the reclassification approach. <i>CECL_p</i> is equal to 1 (0) if a bank qualifies as a non-SRC (SRC) bank in the placebo test period (i.e., 2008) according to SEC’s definition of SRC during that period.

²⁷ With one exception, we extract bank financial data from the “Companies” dataset in S&P Capital IQ Pro, which provides better coverage of the variables we need than the “Regulated Depositories (U.S.)” dataset. As a result, our data item numbers (called “Keyfields”) for the bank financial variables often differ from those of other studies that pull bank financial data from the “Regulated Depositories (U.S.)” dataset (e.g., Wheeler 2021). For example, the Keyfield for total assets (the allowance for loan and lease losses under the incurred loss model) is Keyfield 280297 (280287) in the “Companies” dataset, and thus is what we use in our study, but is Keyfield 215382 (215372) in Wheeler (2021). The one exception is that we extract the CECL day-1 impact variable (SNL Keyfield 319096) from the “Regulated Depositories (U.S.)” dataset because that variable is not available in the “Companies” dataset.

Variable	Definition
<i>ConsLoans</i>	Total consumer loans outstanding (SPCIQ Keyfield 290161).
<i>Dec2019</i>	Indicator equal to 1 during December 2019, and zero otherwise.
<i>EA</i>	Daily indicator equal to 1 for trading days on or after the bank's earnings announcement for Q4 2019, and 0 otherwise.
<i>Feb2020</i>	Indicator equal to 1 from February 1 – February 20, 2020 (that is, the part of the “control” period for the COVID analyses that is in February 2020), and zero otherwise.
<i>IL_Allowance</i>	The allowance for loan and lease losses under the incurred loss model (SPCIQ Keyfield 280287).
<i>Interest</i>	Interest income on loans (SPCIQ Keyfield 280322) averaged over the previous eight quarters.
<i>Jan2020</i>	Indicator equal to 1 during January 2020, and zero otherwise.
<i>ln(Assets)</i>	The natural logarithm of total assets (SPCIQ 280297).
<i>ln(MVE)</i>	The natural logarithm of market value of equity, in \$ millions. Market value of equity is calculated as price per share from CRSP (abs(prc)/cfacpr) multiplied by number of shares outstanding from CRSP (<i>shrout</i> * <i>cfacshr</i>), divided by 1,000.
$[\ln(MVE)]^2$	<i>ln(MVE)</i> squared.
$[\ln(MVE)]^3$	<i>ln(MVE)</i> cubed.
<i>LowTier1</i>	Indicator equal to 1 if a bank's tier 1 risk-based capital ratio (<i>Tier1Ratio</i> , as defined below) is in the lowest quintile among the sample banks, and zero otherwise.
<i>NCO_{t+1}</i>	Net charge-offs as of the end of quarter t+1. Net charge-offs is equal to gross charge-offs (SPCIQ Keyfield 281342) minus recoveries (SPCIQ Keyfield 281380).
$\sum \left(\frac{NCO}{Assets}\right)_{t+1:4}$	Net charge-offs scaled by total assets cumulated over the next four quarters. Net charge-offs is equal to gross charge-offs (SPCIQ Keyfield 281342) minus recoveries (SPCIQ Keyfield 281380).
<i>NetIncome</i>	Net income before discontinued operations (SPCIQ Keyfield 280347).
<i>NIBP</i>	Net income before taxes and loan loss provision, calculated as net income before taxes (SPCIQ Keyfield 280344) plus loan loss provision (SPCIQ Keyfield 280330).
<i>NPL</i>	Nonperforming loans, calculated as nonaccrual loans (SPCIQ Keyfield 281530) plus loans past due 90 days or more but still accruing (SPCIQ Keyfield 281489).
<i>Point</i>	Indicator equal to 1 if the bank's CECL SAB 74 estimate is a point forecast, and zero otherwise.
<i>Post</i>	A dummy variable indicating the treatment period for the capital market benefits analyses. <i>Post</i> is equal to 1 during the treatment period of February 21 – March 24, 2020, and equal to 0 during the control period of January 1 – February 20, 2020.

Variable	Definition
<i>Post_p</i>	A dummy variable indicating the placebo treatment period for the placebo test for the capital market benefits analyses using the 2008–2009 Financial Crisis setting. <i>Post_p</i> is equal to 1 during the placebo treatment period of September 15 – October 17, 2008, and equal to 0 during the placebo control period of July 26 – September 14, 2008.
<i>Pre-EA Return</i>	The bank’s cumulative return in the [-50, -5] trading-day window prior to the earnings announcement.
<i>Price</i>	Price per share from Compustat (prccq).
<i>PriceImpact</i>	Share volume-weighted percent price impact. It is the “PercentPriceImpact_LR_SW” variable from the “Millisecond Intraday Indicators by WRDS” dataset, computed following the methodology in Holden and Jacobsen (2014).
<i>PriorStressTest</i>	An indicator variable equal to 1 if the bank did <i>not</i> participate in the 2020 Comprehensive Capital Analysis and Review (CCAR) stress test but did participate in company-run stress tests under the Dodd-Frank Act and/or CCAR at some point in the past, and 0 otherwise.
<i>RateSensitive</i>	Rate-sensitive assets maturing within one year (SPCIQ Keyfield 280515).
<i>RELoans</i>	Total real estate loans outstanding (SPCIQ Keyfield 290155).
<i>Return</i>	Daily bank-level return from CRSP (ret).
<i>Return[EA day 0 to 10-K/Q+1]</i>	Abnormal stock return, beginning on the day of the earnings announcement through one day after the bank’s 10-K/Q filing. Abnormal return is calculated as the bank’s daily return minus the daily value-weighted market return, cumulated using a buy-and-hold (B&H) and cumulative (CAR) approach.
<i>Shares</i>	Number of shares outstanding from Compustat, in thousands (cshoq*1,000).
<i>Smooth</i>	<p>A measure of the extent to which a bank recently uses loan loss provisions (LLP) to smooth earnings, based on the “SmoothCoeff” measure in Narayanamoorthy and Wheeler (2021). Specifically, Smooth is the firm-specific coefficient β_1 from the following 12-quarter rolling regression (minimum 8 quarters of data are required):</p> $LLP_{i,t} = \alpha + \beta_1 NIBP_{i,t} + \beta_2 \Delta NPL_{i,t-1} + \beta_3 \Delta NPL_{i,t} + \beta_4 \Delta NPL_{i,t+1} + \beta_5 CO_{i,t} + \beta_6 LoanInt_{i,t} + \beta_7 \Delta GDP_t + \epsilon_{i,t}$ <p>LLP is loan loss provision (SPCIQ Keyfield 280330). NIBP is defined above. ΔNPL is change in nonperforming loans during the quarter. CO is gross charge-offs (SPCIQ Keyfield 281342). Except for GDP growth, all other variables are scaled by total loans at the beginning of quarter t (SPCIQ Keyfield 290178).</p>

Variable	Definition
<i>Spread</i>	Time-weighted percent quoted spread during market hours. It is the “QuotedSpread_Percent_tw” variable from the “Millisecond Intraday Indicators by WRDS” dataset, computed following the methodology in Holden and Jacobsen (2014). The weights are based on the amount of time during a trading day that the spreads are in force.
<i>StockVol</i>	The quote-based intraday stock volatility during market hours, which is the “ivol_q” variable from the “Millisecond Intraday Indicators by WRDS” dataset.
<i>Tier1Ratio</i>	Tier 1 risk-based capital ratio (SPCIQ Keyfield 280216).
<i>Turnover</i>	Share turnover, calculated as the daily share volume divided by the market capitalization from CRSP: $vol/(shrout*cfacshr*1000)$.
<i>UE</i>	I/B/E/S street earnings minus the most timely mean consensus street EPS forecast from I/B/E/S, scaled by stock price at fiscal quarter-end.

Figure 1: The CBOE Volatility Index (VIX) During the Sample Period for the COVID Analyses and the Related Placebo Tests

Figure 1A: Daily VIX During the Sample Period for the COVID Analyses

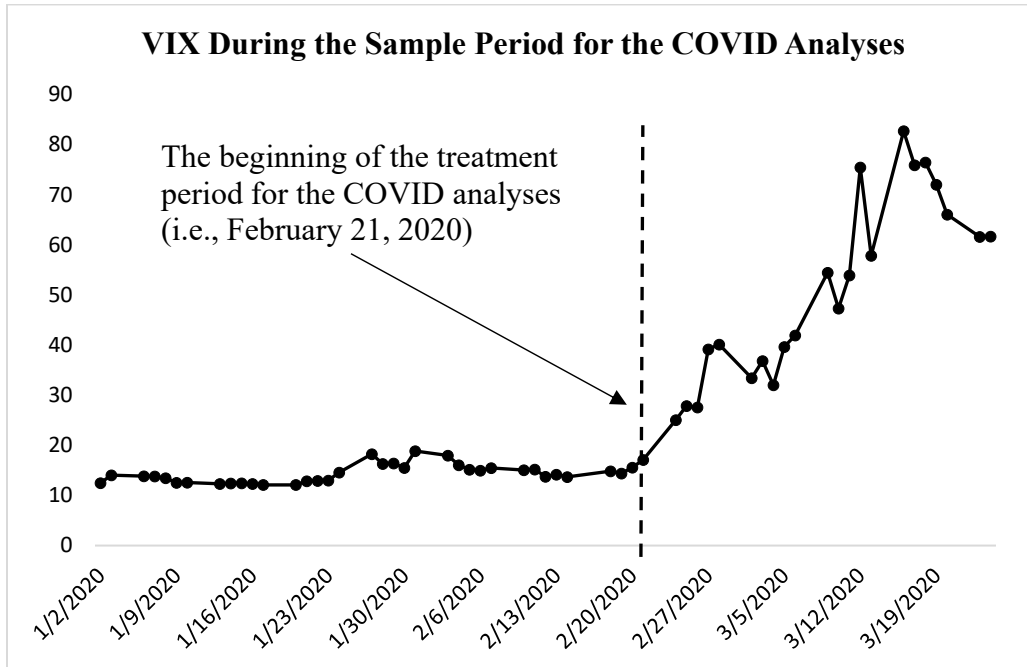


Figure 1B: Daily VIX During the Period for the Placebo Tests

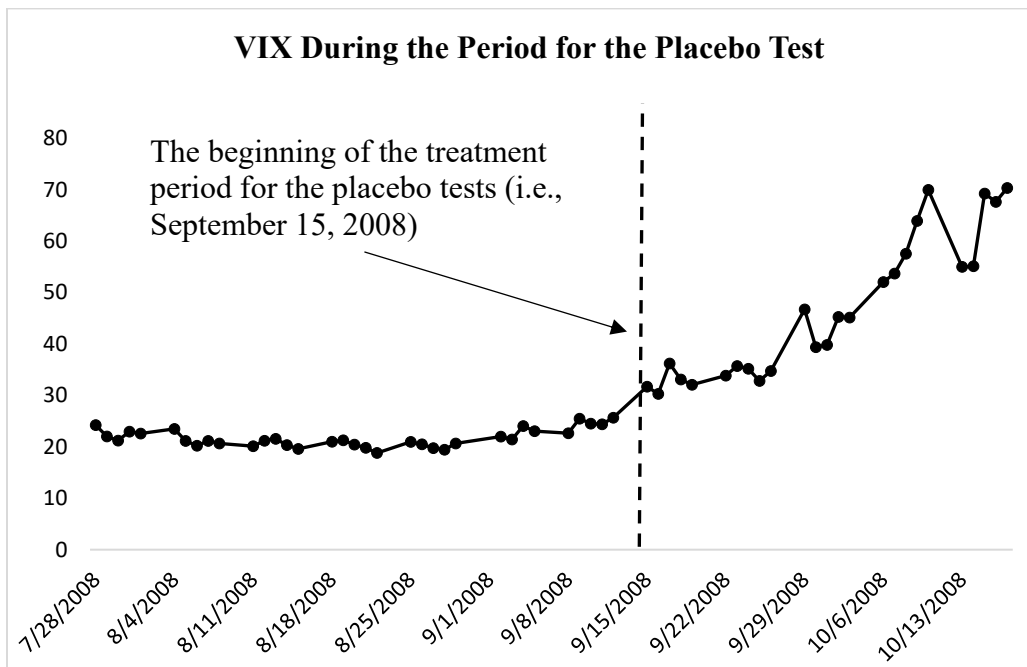


Figure 1A (1B) shows the daily VIX during the sample period for the COVID analyses (the period for the placebo tests).

Table 1: Sample Selection

Part I:	
<u>Sample Selection for the Cross-Sectional Analyses on the CECL Day-1 Impact (Tables 3-5, 7, 8)</u>	
Number of unique publicly traded banks in SNL (SIC codes 6000-6299) with an incurred-loss allowance balance and coverage in CRSP	377
Less: Banks with missing data for variables required in the regressions	28
Number of unique publicly traded banks with data required for the regressions	349
Less: CECL non-adopters	152
Sample of banks used for Tables 4, 5, 7, and 8	197
Less: Banks with insufficient data to compute Smoothing variable	7
Sample of banks used for Table 3	190
Part II:	
<u>Sample Selection for SAB 74 Investor Response Analysis (Table 6)</u>	
Sample of banks used for Tables 4, 5, 7, and 8	197
Less: Banks with less than two disclosed SAB 74 CECL estimates	34
Less: Banks missing data for variables required in the regressions	5
Sample of banks used for Table 6	158
Sample of quarterly observations for 158 banks represented in Table 6	244
<u>Sample Selection for the Covid Analyses (Table 7)</u>	
Number of unique publicly traded banks in SNL (SIC codes 6000-6299) with an incurred-loss allowance balance in SNL and coverage in CRSP	377
Less: CECL adopters with non-calendar-year-end	10
Less: Banks with missing data for variables required in the regressions (including 19 banks missing intra-day data on bid-ask spread)	45
Less: Banks that did not report a SAB 74 estimate until 2020 (i.e., for Q4 2019 or later)	115
Number of unique publicly traded banks with required data represented in Table 7	207
Sample of daily observations for 207 banks represented in Table 7	11,378

Part I of this table presents the sample selection procedures for the sample used to explore whether the CECL day-1 impact is decision useful (i.e., relevant and faithfully representative). Part II presents the sample selection procedures for analyses that explore whether CECL represents new information to investors.

Table 2: Summary Statistics**Panel A: Summary Statistics for the Sample for the CECL Day-1 Impact Analyses**

Variable Name	N	Mean	p25	p50	p75	SD
<u>Dependent Variables</u>						
<i>CECL_Allowance/Assets</i>	197	0.009	0.006	0.008	0.010	0.006
<i>IL_Allowance/Assets</i>	197	0.007	0.004	0.006	0.008	0.004
<i>CECL_Impact/Assets</i>	197	0.002	0.000	0.001	0.003	0.003
<i>Price</i>	197	45.925	22.590	35.250	50.330	48.687
<i>Price_{t+2}</i>	194	35.527	17.240	25.735	40.200	38.954
<i>NPL_{t+1}/Assets_{t+1}</i>	197	0.005	0.003	0.004	0.006	0.005
<i>NPL_{t+4}/Assets_{t+4}</i>	156	0.006	0.002	0.005	0.007	0.005
<i>NCO_{t+1}/Assets_{t+1}</i>	197	0.000	0.000	0.000	0.000	0.001
$\Sigma(NCO/Assets)_{t+1:4}$	155	0.002	0.000	0.001	0.002	0.004
<u>Independent Variables</u>						
<i>Smooth</i>	190	0.066	-0.055	0.017	0.167	0.377
<i>LowTier1</i>	197	0.208	0	0	0	0.407
<i>NPL/Assets</i>	197	0.005	0.002	0.004	0.006	0.005
<i>Interest/Assets</i>	197	0.008	0.007	0.008	0.009	0.003
<i>Assets (thousands)</i>	197	89,700,000	5,646,348	12,100,000	30,600,000	327,000,000
<i>RELoans/Assets</i>	197	0.455	0.380	0.488	0.582	0.183
<i>ConsLoans/Assets</i>	197	0.051	0.004	0.013	0.059	0.105
<i>CECL_Impact/Shares</i>	197	0.537	0.046	0.266	0.617	0.931
<i>IL_Allowance/Shares</i>	197	1.919	0.827	1.310	2.113	2.116
<i>BVE_Adjusted/Shares</i>	197	36.933	21.342	30.750	39.464	31.216
<i>RELoans/Shares</i>	197	115.730	68.757	100.399	145.207	80.099
<i>ConsLoans/Shares</i>	197	16.546	0.956	3.716	11.733	40.173
<i>RateSensitive/Shares</i>	197	121.451	50.066	75.727	131.851	158.525
<i>NIBP/Shares</i>	197	1.328	0.654	0.966	1.548	1.434
<i>NPL/Shares</i>	197	1.533	0.487	0.852	1.527	2.256
<i>RateSensitive/Assets</i>	197	0.366	0.268	0.364	0.447	0.137
<i>NIBP/Assets</i>	197	0.004	0.004	0.004	0.005	0.002

Panel B: Summary Statistics for the SAB 74 Investor Response Analysis

Variable Name	N	Mean	p25	p50	p75	SD
<u>Dependent Variables</u>						
<i>Return[EA day 0 to 10-K/Q+1]B&H</i>	244	-0.043	-0.097	-0.043	0.008	0.088
<i>Return[EA day 0 to 10-K/Q+1]CAR</i>	244	-0.042	-0.097	-0.041	0.012	0.091
<u>Independent Variables</u>						
<i>ΔCECL SAB 74 Estimate(x100)/MVE)</i>	244	0.042	-0.030	0.000	0.175	0.480
<i>ln(1+Analysts)</i>	244	2.216	1.792	2.079	2.890	0.643
<i>ln(MVE)</i>	244	8.047	6.592	7.662	9.103	1.848
<i>Book-to-Market</i>	244	1.140	0.828	1.088	1.407	0.432
<i>Pre-EA Return</i>	244	-0.223	-0.388	-0.256	-0.005	0.224
<i>UE</i>	244	-0.009	-0.013	-0.003	0.001	0.013
<i>Point</i>	244	0.787	1	1	1	0.410

Panel C: Summary Statistics for the Sample for the COVID Analyses

Variable Name	Treatment banks in the control period						Control banks in the control period					
	N	mean	p25	p50	p75	SD	N	mean	p25	p50	p75	SD
<i>Spread</i>	2,176	0.001	0.000	0.001	0.001	0.001	4,550	0.019	0.008	0.014	0.024	0.016
<i>PriceImpact</i>	2,176	0.001	0.000	0.000	0.001	0.001	4,550	0.005	0.000	0.002	0.005	0.014
<i>CECL</i>	2,176	1.000	1.000	1.000	1.000	0.000	4,550	0.000	0.000	0.000	0.000	0.000
<i>MVE</i>	2,176	29,529	2,034	4,204	16,337	72,463	4,550	209	114	190	255	129
<i>Turnover</i>	2,176	0.006	0.003	0.005	0.007	0.004	4,550	0.001	0.000	0.001	0.002	0.002
<i>Tier1Ratio</i>	2,176	12.851	11.060	12.280	13.320	2.645	4,550	13.872	11.950	12.980	15.230	2.777
<i>NPL/Assets</i>	2,176	0.006	0.003	0.005	0.007	0.006	4,550	0.005	0.002	0.003	0.007	0.004
<i>NetIncome/Assets</i>	2,176	0.004	0.003	0.004	0.005	0.002	4,550	0.003	0.003	0.004	0.004	0.001
<i>Interest/Assets</i>	2,176	0.008	0.007	0.008	0.009	0.003	4,550	0.008	0.008	0.008	0.009	0.002
<i>RELoans/Assets</i>	2,176	0.370	0.228	0.410	0.511	0.193	4,550	0.608	0.525	0.610	0.693	0.126
<i>ConsLoans/Assets</i>	2,176	0.087	0.006	0.028	0.087	0.163	4,550	0.028	0.002	0.011	0.027	0.049
<i>Return</i>	2,176	-0.001	-0.009	-0.001	0.008	0.014	4,550	-0.001	-0.008	0.000	0.006	0.016
<i>PriorStressTest</i>	2,176	0.33	0	0	1	0.47	4,550	0	0	0	0	0
<i>CCAR2020</i>	2,176	0.27	0	0	1	0.44	4,550	0	0	0	0	0
<i>EA</i>	2,176	0.604	0	1	1	0.489	4,550	0.493	0	0	1	0.500
<i>10KFiled</i>	2,176	0.416	0	0	1	0.493	4,550	0.412	0	0	1	0.492
<i>StockVol ($\times 10^4$)</i>	2,176	0.001	0.000	0.000	0.000	0.003	4,550	0.142	0.007	0.023	0.080	0.369

Variable Name	Treatment banks in the treatment period						Control banks in the treatment period					
	N	mean	p25	p50	p75	SD	N	mean	p25	p50	p75	SD
<i>Spread</i>	1,472	0.003	0.001	0.002	0.004	0.004	3,180	0.043	0.016	0.032	0.057	0.037
<i>PriceImpact</i>	1,472	0.002	0.000	0.001	0.002	0.003	3,180	0.012	0.002	0.006	0.014	0.028
<i>CECL</i>	1,472	1.000	1.000	1.000	1.000	0.000	3,180	0.000	0.000	0.000	0.000	0.000
<i>MVE</i>	1,472	21,980	1,461	3,133	10,878	55,809	3,180	170	91	150	215	111
<i>Turnover</i>	1,472	0.012	0.007	0.011	0.016	0.006	3,180	0.002	0.001	0.002	0.003	0.004
<i>Tier1Ratio</i>	1,472	12.753	11.150	12.275	13.200	2.532	3,180	13.869	11.980	12.980	15.270	2.755
<i>NPL/Assets</i>	1,472	0.006	0.003	0.005	0.007	0.006	3,180	0.005	0.002	0.003	0.007	0.004
<i>NetIncome/Assets</i>	1,472	0.004	0.003	0.004	0.005	0.001	3,180	0.003	0.002	0.003	0.004	0.001
<i>Interest/Assets</i>	1,472	0.008	0.007	0.008	0.009	0.003	3,180	0.009	0.008	0.009	0.009	0.002
<i>RELoans/Assets</i>	1,472	0.373	0.229	0.419	0.520	0.194	3,180	0.609	0.525	0.618	0.693	0.125
<i>ConsLoans/Assets</i>	1,472	0.087	0.006	0.027	0.089	0.164	3,180	0.030	0.002	0.011	0.027	0.055
<i>Return</i>	1,472	-0.021	-0.060	-0.028	0.021	0.077	3,180	-0.016	-0.048	-0.013	0.011	0.071
<i>PriorStressTest</i>	1,472	0.33	0	0	1	0.47	3,180	0	0	0	0	0
<i>CCAR2020</i>	1,472	0.27	0	0	1	0.44	3,180	0	0	0	0	0
<i>EA</i>	1,472	1.000	1	1	1	0.000	3,180	0.976	1	1	1	0.154
<i>10KFiled</i>	1,472	0.825	1	1	1	0.380	3,180	0.378	0	0	1	0.485
<i>StockVol ($\times 10^4$)</i>	1,472	0.004	0.000	0.000	0.002	0.012	3,180	0.325	0.021	0.084	0.344	0.552

Panel A (B) [C] of this table presents the summary statistics for the sample for the CECL day-1 impact (SAB 74 Investor Response) [COVID] analyses. In Panel A, the number of observations for each variable represents the actual number of banks in the regressions. In Panel A, except for variables with subscripts (e.g., $Price_{t+2}$), the subscript for all other variables is quarter t (as of the end of the fiscal quarter immediately before CECL adoption) and is omitted. In Panel B, except for the dependent variables (which are returns measured over the quarterly reporting window), the subscript for all other variables is quarter t , as of the end of the fiscal quarter. In Panel C, the number of observations for each variable is the total number of bank-return-days (11,378, in total) in the regressions. In Panel C, all non-market variables are measured as of the most recently available quarterly data for bank i on day t . See the Appendix for variable definitions.

Table 3: Determinants of the CECL Day-1 Impact

VARIABLES	Pred.	(1) <i>IL_Allowance/Assets</i>	(2) <i>CECL_Impact/Assets</i>	(3) <i>CECL_Allowance/Assets</i>
<i>NPL/Assets</i>	+	0.099** (2.33)	0.143** (2.30)	0.243*** (2.65)
<i>Interest/Assets</i>	+	0.811*** (9.08)	0.451*** (5.96)	1.258*** (10.69)
<i>Smooth</i>	+	0.001 (1.33)	-0.001* (-1.90)	0.000 (0.26)
<i>LowTier1</i>	-	-0.000 (-0.36)	0.000 (0.98)	0.000 (0.40)
<i>RELoans/Assets</i>	-	-0.002* (-1.66)	-0.001 (-1.03)	-0.004** (-2.17)
<i>ConsLoans/Assets</i>	+	0.008*** (3.15)	0.009*** (3.75)	0.017*** (4.52)
<i>log(Assets)</i>	?	-0.000* (-1.94)	0.000 (1.13)	-0.000 (-0.85)
<i>Constant</i>	?	0.005* (1.69)	-0.005* (-1.96)	0.001 (0.21)
Observations		190	190	190
Adjusted R-squared		0.675	0.595	0.781

Column 1, 2, and 3 of this table presents the analysis of the determinants of incurred loss allowances, the CECL day-1 impact, and CECL allowances, respectively. As described in Table 1, the sample consists of 190 publicly listed U.S. banks that adopted CECL during January 1, 2020 – January 1, 2021. Except for *CECL_Allowance* and *CECL_Impact* (both of which are measured on the CECL adoption date), all other variables are measured at the fiscal-year end immediately before CECL adoption (i.e., one day prior to the CECL adoption date). See the Appendix for variable definitions. All continuous variables are winsorized at the 1st and 99th percentiles prior to estimating the regressions. Standard errors are clustered by bank to address heteroskedasticity. Robust *t*-statistics are reported in parentheses below coefficient estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4: The Usefulness of the CECL Day-1 Impact in Valuing Stocks

VARIABLES	(1) <i>Price_t</i>	(2) <i>Price_t</i>	(3) <i>Price_t</i>	(4) <i>Price_{t+2}</i>	(5) <i>Price_{t+2}</i>	(6) <i>Price_{t+2}</i>
<i>CECL_Impact/Shares</i>			-12.021*** (-4.66)			-10.444*** (-3.41)
<i>IL_Allowance/Shares</i>		-7.428*** (-4.20)	-5.720*** (-3.51)		-4.608** (-2.51)	-3.085** (-1.98)
<i>BVE_Adjusted/Shares</i>	0.119 (0.43)	0.053 (0.21)	0.265 (1.41)	0.135 (0.60)	0.096 (0.46)	0.267 (1.52)
<i>RELoans/Shares</i>	0.082** (2.42)	0.110*** (3.22)	0.082*** (3.28)	0.048 (1.50)	0.065* (1.95)	0.039 (1.47)
<i>ConsLoans/Shares</i>	-0.204*** (-2.62)	-0.064 (-1.02)	0.087 (1.52)	-0.234*** (-2.92)	-0.147* (-1.97)	-0.018 (-0.21)
<i>RateSensitive/Shares</i>	0.036 (0.92)	0.013 (0.44)	-0.025 (-1.01)	0.017 (0.45)	0.002 (0.08)	-0.029 (-1.08)
<i>NIBP/Shares</i>	28.778*** (5.07)	37.085*** (6.09)	34.173*** (7.70)	24.174*** (5.00)	29.323*** (5.49)	26.922*** (6.29)
<i>NPL/Shares</i>	-1.857** (-2.26)	-0.567 (-0.57)	0.413 (0.39)	-1.862* (-1.88)	-1.065 (-0.97)	-0.190 (-0.16)
Constant	-4.335 (-1.13)	-3.417 (-0.95)	-0.397 (-0.16)	-2.373 (-0.68)	-1.798 (-0.54)	1.050 (0.41)
Observations	197	197	197	194	194	194
Adjusted R-squared	0.887	0.902	0.924	0.826	0.835	0.861

This table presents the analysis of the usefulness of the CECL day-1 impact in valuing stocks. As described in Table 1, the sample consists of 197 publicly listed U.S. banks that adopted CECL during January 1, 2020 – January 1, 2021, with 3 banks dropping from the analyses presented in columns 4–6 due to a lack of data on two-quarter-ahead stock price (*Price_{t+2}*). Except for *Price_{t+2}* (which is measured two quarters after the CECL adoption date so the bank’s first Form 10-Q filing after CECL adoption is available to investors) and *CECL_Impact* (which is measured on the adoption date), all other variables are measured as of the fiscal quarter-end immediately before CECL adoption (i.e., one day prior to the CECL adoption date). See the Appendix for variable definitions. All continuous variables are winsorized at the 1st and 99th percentiles prior to estimating the regressions. Standard errors are clustered by bank to address heteroskedasticity. Robust t-statistics are reported in parentheses below coefficient estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 5: The Usefulness of the CECL Day-1 Impact in Predicting Future Credit Losses

Panel A: The Usefulness of the CECL Day-1 Impact in Predicting Future Nonperforming Loans

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	$NPL_{t+1}/Assets_{t+1}$	$NPL_{t+1}/Assets_{t+1}$	$NPL_{t+1}/Assets_{t+1}$	$NPL_{t+4}/Assets_{t+4}$	$NPL_{t+4}/Assets_{t+4}$	$NPL_{t+4}/Assets_{t+4}$
<i>CECL_Impact/Assets</i>			0.780*** (5.29)			0.801*** (3.65)
<i>IL_Allowance/Assets</i>		0.561*** (3.88)	0.423*** (4.29)		0.751*** (3.61)	0.617*** (3.92)
<i>RELoans/Assets</i>	0.003* (1.80)	0.001 (0.34)	0.000 (0.01)	0.002 (0.90)	-0.001 (-0.58)	-0.001 (-0.66)
<i>ConsLoans/Assets</i>	0.015*** (3.14)	0.007 (1.58)	-0.003 (-0.83)	0.009 (1.26)	-0.004 (-0.64)	-0.014** (-2.43)
<i>RateSensitive/Assets</i>	0.004 (1.59)	0.005* (1.79)	0.005** (2.21)	0.005 (1.52)	0.004 (1.14)	0.005 (1.57)
<i>NIBP/Assets</i>	-0.248 (-1.00)	-0.744*** (-2.72)	-0.915*** (-4.33)	-0.119 (-0.28)	-0.735* (-1.95)	-0.936*** (-2.95)
Constant	0.003 (1.62)	0.003 (1.58)	0.003** (2.04)	0.003 (1.26)	0.004* (1.76)	0.004** (2.00)
Observations	197	197	197	155	155	155
Adjusted R-squared	0.073	0.176	0.307	0.022	0.134	0.227

Panel B: The Usefulness of the CECL Day-1 Impact in Predicting Future Net Charge-offs

VARIABLES	(1)	(2)	(3)	(5)	(6)	(7)
	$NCO_{t+1}/Assets_{t+1}$	$NCO_{t+1}/Assets_{t+1}$	$NCO_{t+1}/Assets_{t+1}$	$\sum(NCO/Assets)_{t+1:4}$	$\sum(NCO/Assets)_{t+1:4}$	$\sum(NCO/Assets)_{t+1:4}$
<i>CECL_Impact/Assets</i>			0.120*** (5.51)			0.495*** (5.13)
<i>IL_Allowance/Assets</i>		0.086*** (2.96)	0.065*** (2.81)		0.497*** (4.57)	0.414*** (5.04)
<i>RELoans/Assets</i>	-0.000 (-1.26)	-0.001** (-2.21)	-0.001*** (-2.83)	-0.002 (-1.21)	-0.005** (-2.52)	-0.005*** (-2.90)
<i>ConsLoans/Assets</i>	0.004*** (3.59)	0.003** (2.45)	0.002 (1.29)	0.012** (1.98)	0.003 (0.48)	-0.004 (-0.62)
<i>RateSensitive/Assets</i>	-0.000 (-0.41)	-0.000 (-0.29)	-0.000 (-0.15)	-0.001 (-0.25)	-0.002 (-0.65)	-0.001 (-0.47)
<i>NIBP/Assets</i>	0.194** (2.46)	0.118 (1.54)	0.092 (1.43)	1.010*** (2.75)	0.602** (2.24)	0.479** (2.17)
Constant	-0.000 (-1.36)	-0.000 (-1.52)	-0.000 (-1.08)	-0.002 (-1.39)	-0.001 (-0.87)	-0.001 (-0.74)
Observations	197	197	197	155	155	155
Adjusted R-squared	0.584	0.631	0.691	0.667	0.734	0.782

Panel A (B) of this table presents the analysis of the usefulness of the CECL day-1 impact in predicting future nonperforming loans (net charge-offs). The dependent variable in columns 1–3 (4–6) of Panel A is one- (four-) quarter-ahead nonperforming loans, scaled by total assets. The dependent variable in columns 1–3 of Panel B is one-quarter-ahead net charge-offs, scaled by total assets. The dependent variable in columns 4–6 of Panel B is the cumulative net charge-offs scaled by total assets over the next four quarters. As described in Table 1, the sample consists of 197 publicly listed U.S. banks that adopted CECL during January 1, 2020 – January 1, 2021, although 42 (= 197 minus 155) of them dropped from the analysis presented in columns 4–6 because data on four-quarter-ahead nonperforming loans or net charge-offs were not yet available for these banks. Except for *CECL_Impact* (which is measured on the adoption date), all independent variables are measured as of the fiscal quarter-end immediately before CECL adoption (i.e., one day prior to the CECL adoption date). See the Appendix for variable definitions. All continuous variables are winsorized at the 1st and 99th percentiles prior to estimating the regressions. Standard errors are clustered by bank to address heteroskedasticity. Robust t-statistics are reported in parentheses below coefficient estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Investor Response to CECL SAB 74 Estimates

VARIABLES	<i>Return[EA day 0 to 10-K/Q+1]</i>	
	<i>Buy-and-hold</i> (1)	<i>CAR</i> (2)
<i>ΔCECL SAB 74 Estimate/MVE</i>	-1.859* (-1.71)	-2.008* (-1.74)
<i>ln(1+Analysts)</i>	0.039** (2.45)	0.041** (2.41)
<i>UE</i>	0.984 (1.37)	1.204 (1.62)
<i>ln(MVE)</i>	0.002 (0.33)	0.002 (0.26)
<i>Book-to-Market</i>	0.002 (0.09)	0.002 (0.10)
<i>Pre-EA Return</i>	-0.124** (-2.25)	-0.138** (-2.43)
<i>Point</i>	0.009 (0.75)	0.009 (0.73)
Observations	244	244
Adjusted R-squared	0.160	0.154

This table examines investor response to banks' CECL estimates leading up to adoption. The dependent variable, *Return[EA day 0 to 10-K/Q+1]*, is the bank's abnormal stock return beginning on the day of the earnings announcement through one day after the bank's 10-K/Q filing. Abnormal return is calculated as the bank's daily return minus the daily value-weighted market return, cumulated using a buy-and-hold (B&H) and cumulative (CAR) approach. The variable of interest is *ΔCECL SAB 74 Estimate/MVE*, which is the quarterly change in the banks' CECL estimate, scaled by market value of equity. See the Appendix for variable definitions. Except for returns, all continuous variables are winsorized at the 1st and 99th percentiles prior to estimating the regressions. Quarter fixed effects included in all regressions. Standard errors are clustered by bank. Robust t-statistics are reported in parentheses below coefficient estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Impact of CECL on changes in uncertainty around onset of COVID

VARIABLES	(1)		(2)		(3)		(4)	
	<i>Spread</i>	t-stat	<i>Spread</i>	t-stat	<i>PriceImpact</i>	t-stat	<i>PriceImpact</i>	t-stat
<i>CECL</i> × <i>Post</i>	-0.021***	(-6.48)	-0.010***	(-3.99)	-0.005***	(-6.20)	-0.002**	(-2.26)
<i>Return</i> × <i>Post</i>			0.001*	(1.67)			-0.001	(-1.51)
<i>ln(MVE)</i> × <i>Post</i>			-0.034	(-1.57)			-0.010	(-0.69)
<i>Turnover</i> × <i>Post</i>			-0.001**	(-2.26)			0.000	(0.68)
<i>StockVol</i> × <i>Post</i>			0.005***	(5.75)			0.001	(0.95)
<i>[ln(MVE)]</i> ² × <i>Post</i>			0.078*	(1.82)			0.017	(0.63)
<i>[ln(MVE)]</i> ³ × <i>Post</i>			-0.043**	(-2.04)			-0.009	(-0.65)
<i>Tier1Ratio</i> × <i>Post</i>			-0.000	(-0.47)			0.000*	(1.82)
<i>NPL/Assets</i> × <i>Post</i>			0.001	(1.24)			0.000	(0.20)
<i>Interest/Assets</i> × <i>Post</i>			0.001	(1.01)			0.000	(0.93)
<i>NetIncome/Assets</i> × <i>Post</i>			0.000	(0.69)			0.000	(0.86)
<i>RELoans/Assets</i> × <i>Post</i>			-0.002*	(-1.87)			-0.001*	(-2.00)
<i>ConsLoans/Assets</i> × <i>Post</i>			-0.001	(-1.51)			-0.000	(-1.24)
<i>CCAR2020</i> × <i>Post</i>			0.001	(0.46)			0.001	(1.10)
<i>PriorStressTest</i> × <i>Post</i>			-0.001	(-0.42)			0.000	(0.13)
<i>EA</i> × <i>Post</i>			-0.009*	(-1.78)			0.006*	(1.68)
<i>10KFiled</i> × <i>Post</i>			-0.000	(-0.01)			0.001	(0.96)
<i>Return</i>			-0.000	(-0.76)			0.001	(1.37)
<i>ln(MVE)</i>			-0.238***	(-3.74)			-0.074**	(-2.16)
<i>Turnover</i>			-0.001**	(-2.20)			-0.000	(-1.62)
<i>StockVol</i>			0.001**	(2.49)			0.001***	(3.05)
<i>[ln(MVE)]</i> ²			0.425***	(3.54)			0.125*	(1.99)
<i>[ln(MVE)]</i> ³			-0.161***	(-2.79)			-0.048	(-1.57)
<i>Tier1Ratio</i>			0.008**	(2.25)			0.002	(0.91)
<i>NPL/Assets</i>			0.003	(1.27)			0.000	(0.08)
<i>Interest/Assets</i>			-0.011***	(-2.83)			-0.001	(-0.64)
<i>NetIncome/Assets</i>			0.000	(0.67)			-0.000	(-1.39)
<i>RELoans/Assets</i>			0.014*	(1.79)			0.000	(0.09)
<i>ConsLoans/Assets</i>			0.013	(1.30)			-0.002	(-0.46)
<i>EA</i>			0.001	(0.53)			-0.000	(-0.53)
<i>10KFiled</i>			0.000	(0.20)			-0.000	(-0.48)
Bank & Trading day FE's	Yes		Yes		Yes		Yes	
Observations	11,378		11,378		11,378		11,378	
Adjusted R-squared	0.663		0.718		0.221		0.247	

This table presents the analysis of whether CECL expected credit losses are new information for investors. The dependent variable in columns 1 and 2 (3 and 4) is daily percent quoted bid-ask spread (daily price impact), which is our proxy for information asymmetry (stock liquidity). The sample consists of 11,378 bank-day observations, with 2,176 (1,472) of them from the treatment banks in the control (treatment) period and 4,550 (3,180) of them from the control banks in the control (treatment) period. *CECL* is an indicator variable equal to 1 for our “treatment” banks (which are calendar-year-end non-SRC banks), and 0 for our “control” banks (which are calendar-year-end SRC banks). *Post* is an indicator variable equal to 1 for the “treatment” period of February 21, 2020 – March 24, 2020, and 0 for the “control” period of January 1, 2020 – February 20, 2020. All non-market variables are measured as of the most recently available quarterly data for bank *i* on day *t*. All continuous variables are winsorized at the 1st and 99th percentiles prior to estimating the regressions. Standard errors are clustered by bank and trading day. See the Appendix for variable definitions. *t*-statistics are reported in parentheses below coefficient estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Alternative Specifications Comparing the Usefulness of CECL and IL Allowances in Valuing Stocks

VARIABLES	(1) <i>Price_t</i>	(2) <i>Price_t</i>	(3) <i>Price_{t+2}</i>	(4) <i>Price_{t+2}</i>
<i>CECL_Allowance/Shares</i>		-7.602*** (-6.03)		-5.513*** (-3.62)
<i>IL_Allowance/Shares</i>	-7.428*** (-4.20)		-4.608** (-2.51)	
<i>BVE_Adjusted/Shares</i>	0.053 (0.21)	0.111 (0.48)	0.096 (0.46)	0.124 (0.66)
<i>RELoans/Shares</i>	0.110*** (3.22)	0.102*** (3.30)	0.065* (1.95)	0.062** (2.03)
<i>ConsLoans/Shares</i>	-0.064 (-1.02)	0.062 (1.09)	-0.147* (-1.97)	-0.042 (-0.49)
<i>RateSensitive/Shares</i>	0.013 (0.44)	-0.009 (-0.35)	0.002 (0.08)	-0.016 (-0.56)
<i>NIBP/Shares</i>	37.085*** (6.09)	37.970*** (6.72)	29.323*** (5.49)	30.934*** (6.57)
<i>NPL/Shares</i>	-0.567 (-0.57)	0.294 (0.27)	-1.065 (-0.97)	-0.288 (-0.23)
Constant	-3.417 (-0.95)	-1.887 (-0.59)	-1.798 (-0.54)	-0.465 (-0.16)
Observations	197	197	194	194
Adjusted R-squared	0.902	0.915	0.835	0.849

This table presents the analysis of using alternative specifications to compare the usefulness of CECL allowances and IL allowances in valuing stocks. As described in Table 1, the sample consists of 197 publicly listed U.S. banks that adopted CECL during January 1, 2020 – January 1, 2021, with 3 banks dropping from the analyses presented in columns 4–6 due to a lack of data on two-quarter-ahead stock price (*Price_{t+2}*). Except for *Price_{t+2}*, all other variables are measured at the fiscal quarter-end immediately before CECL adoption (i.e., one day prior to the CECL adoption date). *Price_{t+2}* is measured two quarters after the CECL adoption date (so the bank’s first Form 10-Q filing after CECL adoption is available to investors). See the Appendix for variable definitions. All continuous variables are winsorized at the 1st and 99th percentiles prior to estimating the regressions. Standard errors are clustered by bank to address heteroskedasticity. Robust t-statistics are reported in parentheses below coefficient estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 9: Alternative Specifications Comparing the Usefulness of CECL and IL Allowances in Predicting Future Credit Losses

Panel A: Predicting Future Nonperforming Loans

VARIABLES	(1) <i>NPL_{t+1}/Assets_{t+1}</i>	(2) <i>NPL_{t+1}/Assets_{t+1}</i>	(3) <i>NPL_{t+4}/Assets_{t+4}</i>	(4) <i>NPL_{t+4}/Assets_{t+4}</i>
<i>CECL_Allowance/Assets</i>		0.576*** (5.82)		0.699*** (4.81)
<i>IL_Allowance/Assets</i>	0.561*** (3.88)		0.751*** (3.61)	
<i>RELoans/Assets</i>	0.001 (0.34)	-0.000 (-0.16)	-0.001 (-0.58)	-0.002 (-0.81)
<i>ConsLoans/Assets</i>	0.007 (1.58)	-0.002 (-0.57)	-0.004 (-0.64)	-0.014** (-2.42)
<i>RateSensitive/Assets</i>	0.005* (1.79)	0.005** (2.16)	0.004 (1.14)	0.005 (1.49)
<i>NIBP/Assets</i>	-0.744*** (-2.72)	-0.972*** (-4.31)	-0.735* (-1.95)	-0.965*** (-2.98)
Constant	0.003 (1.58)	0.003* (1.87)	0.004* (1.76)	0.004** (2.02)
Observations	197	197	155	155
Adjusted R-squared	0.176	0.298	0.134	0.231

Panel B: Predicting Future Net Charge-offs

VARIABLES	(1) <i>NCO_{t+1}/Assets_{t+1}</i>	(2) <i>NCO_{t+1}/Assets_{t+1}</i>	(3) $\sum(NCO/Assets)_{t+1:4}$	(4) $\sum(NCO/Assets)_{t+1:4}$
<i>CECL_Allowance/Assets</i>		0.089*** (4.89)		0.449*** (6.17)
<i>IL_Allowance/Assets</i>	0.086*** (2.96)		0.497*** (4.57)	
<i>RELoans/Assets</i>	-0.001** (-2.21)	-0.001*** (-2.78)	-0.005** (-2.52)	-0.005*** (-3.03)
<i>ConsLoans/Assets</i>	0.003** (2.45)	0.002 (1.37)	0.003 (0.48)	-0.003 (-0.61)
<i>RateSensitive/Assets</i>	-0.000 (-0.29)	-0.000 (-0.14)	-0.002 (-0.65)	-0.001 (-0.52)
<i>NIBP/Assets</i>	0.118 (1.54)	0.083 (1.30)	0.602** (2.24)	0.467** (2.12)
Constant	-0.000 (-1.52)	-0.000 (-1.26)	-0.001 (-0.87)	-0.001 (-0.71)
Observations	197	197	155	155
Adjusted R-squared	0.631	0.686	0.734	0.782

Panel A (B) of this table presents the analysis of using alternative specifications to compare the usefulness of CECL and IL allowances in predicting future nonperforming loans (net charge-offs). The dependent variable in columns 1–2 (3–4) of Panel A is one- (four-) quarter-ahead nonperforming loans, scaled by total assets. The dependent variable in columns 1–2 of Panel B is one-quarter-ahead net charge-offs, scaled by total assets. The dependent variable in columns 3–4 of Panel B is the cumulative net charge-offs scaled by total assets over the next four quarters. The sample consists of 197 banks that adopted CECL during January 1, 2020 – January 1, 2021, although 42 of them dropped from the analysis presented in columns 4–6 because data on four-quarter-ahead nonperforming loans or net charge-offs were not yet available. Except for *CECL_Impact* (which is measured on the CECL adoption date), all other independent variables are measured one day prior to the adoption date. See the Appendix for variable definitions. All continuous variables are winsorized at the 1st and 99th percentiles prior to estimating the regressions. Standard errors are clustered by bank to address heteroskedasticity. Robust t-statistics are reported in parentheses below coefficient estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 10: Placebo and Pre-Trend Tests for the COVID Analyses

Panel A: Placebo Test Using the “Retain Classification Approach”

VARIABLES	(1)		(2)		(3)		(4)	
	<i>Spread</i>	t-stat	<i>Spread</i>	t-stat	<i>PriceImpact</i>	t-stat	<i>PriceImpact</i>	t-stat
<i>CECL</i> × <i>Post_p</i>	-0.007***	(-3.51)	0.002	(0.70)	-0.001	(-0.74)	0.001	(0.27)
<i>Return</i> × <i>Post_p</i>			0.002**	(2.51)			-0.000	(-0.53)
<i>ln(MVE)</i> × <i>Post_p</i>			0.064***	(2.71)			0.045*	(1.89)
<i>Turnover</i> × <i>Post_p</i>			-0.000	(-0.33)			0.001	(1.03)
<i>StockVol</i> × <i>Post_p</i>			0.001	(0.34)			0.002	(1.32)
<i>[ln(MVE)]²</i> × <i>Post_p</i>			-0.136***	(-2.88)			-0.082*	(-1.76)
<i>[ln(MVE)]³</i> × <i>Post_p</i>			0.071***	(2.92)			0.040	(1.66)
<i>Tier1Ratio</i> × <i>Post_p</i>			0.002	(1.67)			0.000	(0.09)
<i>NPL/Assets</i> × <i>Post_p</i>			0.000	(0.31)			-0.000	(-0.54)
<i>Interest/Assets</i> × <i>Post_p</i>			0.000	(0.29)			0.000	(0.19)
<i>NetIncome/Assets</i> × <i>Post_p</i>			0.001*	(1.74)			0.001	(1.47)
<i>RELoans/Assets</i> × <i>Post_p</i>			0.001	(0.53)			0.001	(1.20)
<i>ConsLoans/Assets</i> × <i>Post_p</i>			0.000	(0.42)			-0.001	(-1.46)
<i>EA</i> × <i>Post_p</i>			0.004	(0.65)			0.001	(0.29)
<i>10KFiled</i> × <i>Post_p</i>			0.001	(0.18)			0.001	(0.29)
<i>Return</i>			-0.000	(-0.53)			0.000	(0.21)
<i>ln(MVE)</i>			-0.060	(-0.53)			-0.058	(-0.78)
<i>Turnover</i>			0.001	(1.61)			0.000	(0.34)
<i>StockVol</i>			0.007***	(4.50)			0.003*	(1.79)
<i>[ln(MVE)]²</i>			0.080	(0.37)			0.093	(0.65)
<i>[ln(MVE)]³</i>			-0.023	(-0.21)			-0.035	(-0.51)
<i>Tier1Ratio</i>			0.009	(1.21)			-0.005	(-0.53)
<i>NPL/Assets</i>			0.002	(1.42)			-0.002	(-0.51)
<i>Interest/Assets</i>			-0.018*	(-1.79)			-0.008	(-0.96)
<i>NetIncome/Assets</i>			-0.001	(-0.37)			-0.001	(-0.79)
<i>RELoans/Assets</i>			-0.014	(-0.89)			-0.022**	(-2.07)
<i>ConsLoans/Assets</i>			0.008	(0.30)			0.004	(0.12)
<i>EA</i>			0.001	(0.31)			0.001	(0.20)
<i>10KFiled</i>			0.003	(1.06)			0.001	(0.50)
Bank & Trading day FE's	Yes		Yes		Yes		Yes	
Observations	5,742		5,742		5,742		5,742	
Adjusted R-squared	0.694		0.720		0.147		0.172	

Panel B: Placebo Test Using the “Reclassify Approach”

VARIABLES	(1)		(2)		(3)		(4)	
	<i>Spread</i>	t-stat	<i>Spread</i>	t-stat	<i>PriceImpact</i>	t-stat	<i>PriceImpact</i>	t-stat
<i>CECL_p × Post_p</i>	-0.001	(-0.16)	0.007	(1.15)	0.001	(0.42)	0.001	(0.19)
<i>Return × Post_p</i>			0.002**	(2.46)			-0.000	(-0.19)
<i>ln(MVE) × Post_p</i>			0.025	(0.64)			0.039	(1.37)
<i>Turnover × Post_p</i>			-0.000	(-0.10)			0.001	(1.07)
<i>StockVol × Post_p</i>			0.000	(0.08)			0.002	(1.14)
<i>[ln(MVE)]² × Post_p</i>			-0.062	(-0.84)			-0.069	(-1.32)
<i>[ln(MVE)]³ × Post_p</i>			0.035	(0.98)			0.033	(1.27)
<i>Tier1Ratio × Post_p</i>			0.003	(1.65)			0.000	(0.06)
<i>NPL/Assets × Post_p</i>			0.000	(0.23)			-0.000	(-0.38)
<i>Interest/Assets × Post_p</i>			0.001	(0.42)			0.000	(0.32)
<i>NetIncome/Assets × Post_p</i>			0.002*	(1.97)			0.002*	(1.68)
<i>RELoans/Assets × Post_p</i>			0.001	(0.45)			0.001	(1.03)
<i>ConsLoans/Assets × Post_p</i>			0.000	(0.11)			-0.001	(-1.44)
<i>EA × Post_p</i>			0.004	(0.54)			0.002	(0.29)
<i>10KFiled × Post_p</i>			0.001	(0.18)			0.000	(0.07)
<i>Return</i>			-0.000	(-0.08)			-0.000	(-0.02)
<i>ln(MVE)</i>			-0.032	(-0.25)			-0.078	(-1.09)
<i>Turnover</i>			0.001	(1.37)			0.000	(0.23)
<i>StockVol</i>			0.007***	(4.28)			0.002	(1.52)
<i>[ln(MVE)]²</i>			0.044	(0.18)			0.135	(0.98)
<i>[ln(MVE)]³</i>			-0.010	(-0.09)			-0.059	(-0.88)
<i>Tier1Ratio</i>			0.010	(1.23)			-0.005	(-0.63)
<i>NPL/Assets</i>			0.001	(0.73)			-0.002	(-0.49)
<i>Interest/Assets</i>			-0.017**	(-2.22)			-0.008	(-1.04)
<i>NetIncome/Assets</i>			-0.002	(-0.94)			-0.001	(-0.67)
<i>RELoans/Assets</i>			-0.007	(-0.45)			-0.016*	(-1.80)
<i>ConsLoans/Assets</i>			0.029	(1.26)			0.013	(0.38)
<i>EA</i>			0.003	(0.78)			0.002	(0.42)
<i>10KFiled</i>			0.003	(1.19)			0.003	(1.35)
Bank & Trading day FE's	Yes		Yes		Yes		Yes	
Observations	5,546		5,546		5,546		5,546	
Adjusted R-squared	0.699		0.726		0.146		0.167	

Panel C. Replicating the Main COVID Analyses After Expanding the Control Period

VARIABLES	(1) <i>Spread</i>	(2) <i>PriceImpact</i>
<i>CECL × Post</i>	-0.010*** (-4.13)	-0.002*** (-3.66)
The same set of control variables as in Table 6, and their interactions with <i>Post</i>	Yes	Yes
Bank FEs	Yes	Yes
Day FEs	Yes	Yes
Observations	27,598	27,598
Adjusted R-squared	0.698	0.218

Panel D. Examining Pre-Treatment Period Trends

VARIABLES	(2) <i>Spread</i>	(4) <i>PriceImpact</i>
<i>Feb2020*CECL</i>	-0.000 (-0.08)	-0.001 (-1.55)
<i>Jan2020*CECL</i>	0.002 (1.20)	-0.000 (-0.90)
<i>Dec2019*CECL</i>	0.003** (2.11)	0.002*** (2.65)
The same set of control variables as in Table 6, and their interactions with <i>Dec2019</i> , <i>Jan2020</i> , and <i>Feb2020</i> , respectively.	Yes	Yes
Bank FEs	Yes	Yes
Day FEs	Yes	Yes
Observations	22,946	22,946
Adjusted R-squared	0.673	0.159

Panel A (B) of this table presents the placebo analysis of the COVID analyses using the “retain classification approach” (“reclassify approach”). The dependent variable in column 1 (2) is daily percent quoted bid-ask (daily price impact). The sample consists of 5,742 (5,546) bank-day observations in Panel A (B). In Panel A, we retain banks’ SRC classification from 2020 and use this same classification during the placebo period; thus, in Panel A, *CECL* is an indicator variable equal to 1 for our “treatment” banks (which are calendar-year-end non-SRC banks), and 0 for our “control” banks (which are calendar-year-end SRC banks). In Panel B, we reclassify banks as SRC and non-SRC during the placebo period (July 26 – October 17, 2008) using the SEC’s classification during that period. $Post_t$ is an indicator variable equal to 1 for the placebo treatment period of September 15 – October 17, 2008, and 0 for the placebo control period of July 26 – September 14, 2008.

Panels C and D examine trends in bid-ask spreads and stock illiquidity prior to the onset of COVID to determine whether evidence exists that casts doubt on the parallel trends assumption. Panel C expands the control period to range from September 1, 2019 to February 20, 2020, and replicates our main COVID analyses. Panel D presents the analysis of pre-treatment period trends in bid-ask spread and stock illiquidity during the last three months of the expanded

control period (i.e., prior to the onset of COVID), from December 1, 2019 to February 20, 2020. We create indicator variables for each of these three months — *Dec2019*, *Jan2020*, *Feb2020*, respectively, and replace each occurrence of the indicator variable *Post* in equation 4 (including its occurrence in the interaction terms) with these three indicator variables.

All continuous variables are winsorized at the 1st and 99th percentiles prior to estimating the regressions. Standard errors are clustered by bank and trading day. See the Appendix for variable definitions. *t*-statistics are reported in parentheses below coefficient estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.