How Does Recognition of Forward-Looking Estimates Affect Learning about the Macroeconomy? Evidence from CECL

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Abstract

We use the adoption of current expected credit loss reporting for banks as a setting to examine how recognition of managers' forward-looking estimates affects their learning from stock prices. We posit that recognition of banks' expected credit losses can reduce managerial learning in two ways. First, managers are forced to invest in information systems that allow them to generate decision-useful information and to rely less on alternative sources, such as stock price. Second, the disclosure of expected credit losses reduces incentives for investors to privately collect and trade based on this information, thereby reducing the informativeness of stock prices for banks' lending decisions. We find robust evidence that bank managers learn from stock prices under the incurred loss model and that this learning is attenuated under the expected credit loss model. The results vary with banks' information advantage over equity market participants and are robust to alternative treatment and control groups and measurement approaches. We present some evidence that the reduction in learning hurts banks' lending efficiency.

JEL Classification: M41, D83, G21
Keywords: Forward-Looking Estimates, Managerial Learning, Expected Credit Losses

1. Introduction

For at least a century, practitioners and academics have debated whether and to what extent the numbers recognized on firms' financial statements should be determined by historical transaction amounts or managers' forward-looking estimates (Paton 1922). Traditionally, the debate revolves around the trade-off between relevance and reliability. Managers' forward-looking estimates can provide information that is more relevant than historical cost amounts for users' decisions but less reliable due to the uncertain nature of estimates (Barth, Beaver, and Landsman 1996; Watts 2003).[1] In this paper, we highlight a cost of relying on managers' forward-looking estimates that, to the best of our knowledge, has not been examined in the literature so far: the extent to which managers can learn from stock prices.[2]

Hayek (1945) established that financial markets aggregate the decentralized information locally possessed by a myriad of market participants. Building on this insight, the managerial learning literature argues that equity markets provide aggregated information to managers in a timely fashion and thereby influence managers' information set and real investment decisions. Recent work in this literature suggests that mandatory disclosure regulation may reduce equity market participants' incentives to privately collect and trade based on information related to the mandatory disclosure; as a result, it may reduce managers' learning from stock prices (Jayaraman and Wu 2019; Pinto 2023). However, it remains unclear exactly how managers' mandatory disclosure of information (that managers do know for certain and thus could not learn about)

[1] Some papers in this literature have focused on level 3 fair value measurement, which is an application of the use of managers' forward-looking estimates. However, there are also other uses of managers' forward-looking estimates, such as the accounting for warranty provisions, bad debt, and, as examined in this paper, expected credit losses.

[2] When using the term "historical cost" accounting, we do not refer solely to measuring financial statement items via past transaction amounts. Rather, we follow the prior literature and include certain forward-looking estimates, such as depreciation or impairments (i.e., "amortized cost"). We could be more precise by referring to an extension in the degree of the use of forward-looking estimates. However, given that the "historical cost" terminology is standard in prior literature, we adhere to it.

disincentivizes equity market participants' private collection of information (that managers do not know for certain and thus could learn about). Our focus on managers' reporting of forward-looking estimates addresses this conundrum, as such estimates, by definition, require managers to forecast highly uncertain future outcomes (that managers do not know for certain and thus could learn about) for which aggregated equity market participants' decentralized local information likely is incrementally useful to managers' private information.

Three challenges make it difficult to identify how the recognition of managers' forward-looking estimates affects managerial learning. First, accounting standards usually mandate recognition of managers' forward-looking estimates for a particular asset or liability for all firms, which precludes the use of cross-sectional variation to isolate the effect of the change in measurement attribute from that of other contemporaneous variable realizations. Second, in settings with cross-sectional variation in the use of different measurement approaches, managers typically can choose to employ their favored measurement approach.[3] This raises concerns that the determinants of their choice, rather than the recognition of managers' forward-looking estimates, are driving the results. Third, standard setters often require firms to disclose managers' forward-looking estimates only in the footnotes and do not require firms to recognize them in the financial statements.[4] It is difficult to derive general conclusions from such settings because preparers (users) likely invest less in preparing (understanding) disclosed amounts than recognized amounts (Schipper 2007; Müller, Riedl, and Sellhorn 2015; Donovan, McMartin, and Phillips 2023). We address these concerns by examining a recent setting where some firms within an industry were forced to recognize managers' forward-looking estimates, while other firms within the same

[3] An example is SFAS 159 which "permits entities to choose to measure many financial instruments and certain other items at fair value" (p. 5).
[4] An example is SFAS 107 which requires banks to disclose (but not to recognize) fair value estimates for loans.

industry were not: the adoption of the Financial Accounting Standards Board (FASB) Accounting Standards Update (ASU) 2016-13, which mandates the use of the current expected credit loss model (CECL).

CECL requires banks to recognize *expected* credit losses incremental to *incurred* credit losses (ICL). By doing so, the CECL model shifts the basis of banks' financial reporting for loans from historical cost to managers' forward-looking estimates. We focus on the CECL setting to test our research question for three reasons. First, the staggered adoption of the CECL model addresses the three concerns outlined in the previous paragraph. While larger banks exceeding one of three size-related thresholds had to adopt CECL by 2020Q1, banks below these thresholds had to adopt by 2023Q1. This allows us to examine how managerial learning from stock prices changed for banks above relative to those below the thresholds around 2020Q1 and attribute the results more directly to changes in forward-looking estimates. Second, bank lending is systemically important, and the switch from the incurred to the expected credit loss reporting model is a hotly debated topic in financial reporting (Beatty and Liao 2021). Third, banks are excluded from prior work examining managerial learning because, in contrast to industrial firms, their investment is not captured by capital expenditures and research and development. Studying banks enables us to contribute novel evidence on whether and how banks learn about their investment prospects from stock markets.[5]

We hypothesize that CECL reduces managerial learning from stock prices in two ways. First, Kim, Kim, Li, and Kleymenova (2023) show that CECL induced bank managers to invest

[5] One exception is De George, Donovan, Phillips, and Wittenberg Moerman (2023), which examines whether bank lenders learn about the credit risk associated with *borrowers* from the *borrowers'* stock price. Leveraging the M&A setting, they show that interest rates charged on syndicated loans are associated with M&A returns and conclude that banks learn from borrowers' stock prices. In our study, we propose that banks learn about lending investment opportunities from their own stock price and examine whether disclosure of expected credit losses affects this relation.

more in their internal information systems and allowed them to form expectations more accurately. While forecasting expected credit losses is inherent to banks' lending decision-making, investment in internal information systems can both increase information available to managers (Shroff 2017) and reduce internal information frictions (Gelsomin 2024). This investment in internal systems would decrease their reliance on alternative information sources, such as their own stock price. Second, CECL forces bank managers to recognize their private expectations about credit losses over the lifetime of the loans they issue. This recognition reduces the information advantage outsiders could obtain by privately collecting information about future credit losses; thus, it reduces these outsiders' ability to trade profitably based on such privately collected information.[6] This reduction in information-based trading reduces the extent to which banks' stock prices reveal decision-relevant information to managers. For this reason, managers rely less on their banks' stock prices when making investment decisions (Gao and Liang 2013). CECL is an especially salient setting for this learning-from-stock-price channel since future loan performance is largely determined by future macroeconomic conditions (Mian and Sufi 2010; Khan and Ozel 2016). When forecasting future macroeconomic conditions, managers do not tend to have an information advantage over outsiders (Hutton, Lee, and Shu 2012; Vidinova 2024), which means that future macroeconomic conditions are an important piece of information for managers to infer from their banks' stock prices. Indeed, consistent with the predictions of rational inattention theory (Maćkowiak, Matějka, and Wiederholt 2023), managers ignore publicly available macroeconomic information and instead rely on simple heuristics, such as stock price, to learn about the macroeconomy (Coibion, Gorodnichenko, and Kumar 2018; Goldstein, Liu, and Yang 2023).

[6] Consistent with this prediction, Bonsall, Schmidt, and Xie (2022) find that CECL decreases the coverage and forecast accuracy of analysts who cover banks.

We employ a difference-in-difference design that exploits the staggered adoption of CECL in the US between 2020 and 2023. Large (small) banks that adopted CECL in 2020 (2023) constitute our treatment (control) group. We examine the association between future bank investment, as proxied by growth in bank lending, and Tobin's Q to capture the extent to which bank managers learn from their banks' stock prices (Chen, Goldstein, and Jiang 2007). Findings in recent literature suggest that such learning takes place. Specifically, Begenau, Bigio, Majerovitz, and Vieyra (2020) develop a Q-theory for banks and demonstrate that Tobin's Q predicts bank profits and reflects crisis and net worth declines better than book leverage. Further, Wheeler (2021) provides evidence that investors incorporate in stock prices information about future credit losses that are not reflected in banks' financial reporting records. If the expected credit loss information in prices is incremental to banks' private information and relevant for their future lending decisions, then banks' lending should vary positively with Tobin's Q.

We document a robust positive association between Tobin's Q and changes in future bank lending. This is consistent with our first prediction that bank managers use expected credit loss information gathered and incorporated into banks' stock prices by investors. Importantly, we find that CECL attenuates this association. In terms of economic magnitude, we find that treatment banks' lending-Q sensitivity falls by 0.245 standard deviations more for treatment than for control banks following CECL adoption. When plotting the treatment effect over the different year-quarters of our sample, we find no evidence of a diverging trend in the lending-Q sensitivity between treatment and control banks prior to the adoption of CECL. Thus, the parallel trends assumption underlying our difference-in-differences design appears reasonable in our setting. In total, these findings indicate that the recognition of forward-looking estimates prompted by CECL significantly reduced bank managers' learning from stock prices.

Next, we examine how the effect varies with different types of loans to provide evidence of the mechanism underlying our main results. If CECL reduces banks' lending-Q sensitivity by decreasing the amount of useful information that bank managers can learn from stock prices, we expect our results to be stronger (weaker) when banks have a smaller (larger) information advantage over outsiders about the parameters that determine the performance of their loan portfolios. We operationalize banks' information advantage over outsiders in two ways. First, even under ICL, banks record an allowance for credit expected losses for short-term homogenous loans (i.e., those with a maturity of less than one year) (Ryan 2019). As a result, CECL does not significantly change the accounting representation of such loans and thereby does not change managers' information advantage over outsiders. Second, homogenous (heterogenous) loans tend to be managed at the portfolio (individual loan) level. Their management involves the collection of macroeconomic (loan-specific) information for which managers do not (do) tend to have an information advantage over outsiders (Hutton et al. 2012; Vidinova 2024). Our results are consistent with the crowding-out mechanism: we find that CECL significantly decreases the lending-Q sensitivity for long-term homogenous loans but not for short-term homogenous loans (for which the accounting did not significantly change) or heterogenous loans (for which managers' can learn less from stock prices).

Ex ante, it is unclear how CECL affects banks' overall lending efficiency. On the one hand, CECL induced banks to invest more in their financial reporting systems, which increases the quality of information available to bank managers and thereby increases investment efficiency (Kim et al. 2023; Gelsomin 2024). On the other hand, the evidence so far indicates that CECL reduces managerial learning from stock prices, which decreases the quality of information available to bank managers and thereby reduces investment efficiency (Gao and Liang 2013).

Consistent with the reduction in managers' learning from stock prices affecting their ability to deploy capital to lending opportunities, we document a decrease in the profitability of banks that also experience a decrease in lending-Q sensitivity, which is driven by a decrease in efficiency (measured as asset turnover). Consistent with Granja and Nagel (2023), we do not find evidence that the fall in profitability and efficiency results from CECL inducing banks to decrease the riskiness of their lending practices.

We examine the robustness of our results to a variety of design changes to address several empirical concerns. First, our treatment group of large US banks might be systematically different from our control group of small US banks in a way that confounds our results. To address this concern, we re-estimate our regressions after (1) using a sample of entropy-balanced EU and UK banks instead of small US banks as our control group and (2) examining CECL's effects on small relative to large banks when small banks had to adopt in 2023Q1. Second, mechanical day-one effects of CECL and accounting differences that exist after CECL adoption could confound our measurement of the denominator of Tobin's Q because expected credit loss recognition reduces the book value of equity of adopting banks relative to that of non-adopting banks. To address this concern, we (1) adjust the denominator and numerator in the Tobin's Q calculation for any accrual accounting effects pertaining to loan provisioning and (2) use the natural logarithm of banks' market capitalization scaled by total assets as an alternative proxy (Pinto 2023). Third, we alter the measurement of lending growth. Fourth, we acknowledge that our post-CECL period for the earliest adopting banks is affected by the outbreak of COVID-19. In addition to employing the 2023Q1 setting described above (which is not directly affected by the COVID-19 outbreak), we address concerns that COVID-19 confounds our inferences by (1) dropping the quarter with the highest uncertainty surrounding the COVID-19 outbreak (2020Q2), (2) removing all COVID-19 relief PPP (Paycheck Protection Program) lending from our lending change variable measurement (as PPP lending disproportionally affected the lending decisions of small banks), and (3) directly controlling for the level of PPP lending (Ballew, Nicoletti, and Stuber 2022). Our inferences remain unchanged across all robustness tests.

Our analysis is subject to several limitations. First, it is possible that our treatment and control banks systematically differ in ways that confound our results. While we try to address this concern by examining the parallel trends assumption underlying our difference-in-differences design, employing different control and treatment groups, and controlling for a range of observables, we cannot fully rule it out. Second, investors and managers have correlated underlying information sets, which drives a *positive* relation between bank managers' lending and investors' trading decisions (Sani, Shroff, and White 2023; Gelsomin and Hutton 2023). We attempt to address this concern by employing a differences-in-differences design documenting that CECL *negatively* affects banks' lending-Q sensitivity and providing evidence of cross-sectional variation and consequences consistent with the learning channel. However, we cannot fully rule out the possibility that an unspecified correlated omitted fundamental factor is driving the correlation between CECL adoption and lending-Q sensitivity we document. Third, US banks had the option of delaying CECL implementation for up to two years post the required adoption date, which could induce selection bias. We find that 18% of banks took this option, and we confirm that our results are insensitive to including or removing them from our sample. Even so, one should be cautious about generalizing our inferences to deferring banks. Fourth, ASU 2016-13 mandates the types of forward-looking estimates that are specific to the standard and whose underlying (loan defaults) is sensitive to macroeconomic developments (about which managers do not have a clear information advantage over outsiders). Our inferences might not generalize to other standards that mandate different types of forward-looking estimates and about whose underlying managers do have an information advantage over outsiders (such as impairment charges resulting from changes in how the firm uses the asset).

With these limitations in mind, we contribute to three strands of literature. The first literature examines the benefits and costs of forward-looking estimates relative to historical cost accounting.[7] Prior work on forward-looking estimates predominantly examines whether the recognition and disclosure of forward-looking estimates *benefits* equity investors and lenders by improving the relevance of accounting information.[8] We contribute to this literature by providing evidence of a previously unexamined *cost* of recognizing forward-looking estimates: decreased managerial learning from stock prices. Our results suggest that the recognition of forward-looking estimates can reduce investors' collection of and trading based on certain types of information (here macroeconomic information) and that this reduction in information-based trading reduces managerial learning from stock price.

The second literature examines whether and how financial reporting regulation affects managerial learning from stock price. Jayaraman and Wu (2019) and Pinto (2023) find that financial reporting regulation crowds out private information collection and incorporation into stock prices and thereby hurts investment efficiency.[9,10] However, these studies do not address the question of how the reporting of information that managers do know can crowd out information

[7] For a review of this literature see Hodder, Hopkins, and Schipper (2014).
[8] See, e.g., Barth et al. (1996), Song, Thomas, and Yi (2010), and Demerjian, Donovan, and Larson (2016).
[9] Three papers focus on the effect of *voluntary* disclosure on managerial learning from stock price. Zuo (2016) and Jayaraman and Wu (2020) find that managers use voluntary disclosures to elicit and learn from market reactions to these disclosures. Binz, Ferracuti, and Lind (2023b) find that managers can use voluntary disclosure to make it more attractive for investors to collect and price information the managers want to learn about.
[10] Studies have also examined disclosure outlets *outside* of financial reporting that affect managerial learning. For example, Sani et al. (2023) find that increases in mandatory mutual fund portfolio disclosure frequency decreased managerial learning from price. In addition, Binz et al. (2023b) find that central bank economic transparency reduces investment sensitivity to stock prices.

that managers can learn from (i.e., information they do not already know). We contribute to this literature by providing evidence that the switch in recognition from historical cost accounting (which is based on information that managers know) to forward-looking estimates (about which equity market participants likely possess information that managers do not know) deprives stock prices of information that is relevant to bank managers' lending decisions.[11] We also respond to Gelsomin and Hutton (2023), who call for managerial learning research that clearly identifies what managers are learning. We show evidence consistent with managers learning information about the macroeconomy from stock prices and using that information in their lending decisions.

The third contemporaneous and growing literature examines the consequences of the FASB's switch from the ICL to the ECL model through ASU 2016-13.[12] We contribute to this literature by highlighting reduced bank manager learning from stock prices as a cost of switching from ICL to CECL.[13] In particular, we complement Kim et al. (2023), who find that CECL improved banks' internal information production. We do so by providing evidence that this increase in internal information production is at least partially if not more than offset by a decline in the amount of information externally gathered by investors and available to managers through their banks' stock price. Our findings align with those in Bonsall et al. (2022) that the informativeness of analysts' loan loss forecasts declines following the adoption of CECL, which is consistent with a reduction in the usefulness of information produced outside of the bank.

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[11] Our study also responds to Roychowdhury, Shroff, and Verdi's (2019) calls for more research on (1) how financial accounting affects managerial learning from stock prices and the mechanisms underlying this relation (p. 4), and (2) how requirements to disclose proprietary information (here, the forward-looking estimates CECL requires) affect managers' investment decisions (p. 19).

[12] See, e.g., Huber (2021), Bonsall et al. (2022), Basu, Roychowdhury, and Sinha (2023), Chen, Dou, Ryan, and Zou (2023), Kim et al. (2023), Granja and Nagel (2023), and Mahieux, Sapra, and Zhang (2023).

[13] Our paper also speaks to the role of market discipline in the context of banking supervision (e.g., Nier and Baumann 2006). Market discipline over banks relates to equity holders demanding a commensurate risk premium to mitigate excessive risk-taking by bank managers. If managers become less responsive to market dynamics because of CECL, this reduces equity holders' ability to discipline managers via influencing market prices.

2. Related Literature and the CECL Setting

2.1. Forward-Looking Estimates

The literature examining the use of forward-looking estimates in financial reporting has focused on its costs and benefits relative to simply stating assets and liabilities at historical transaction amounts. Forward-looking estimates can increase the relevance of information (i.e., the ability of information to affect financial statement users' decisions), but they come at some cost of reliability (i.e., representational faithfulness and verifiability) (Hodder et al. 2014). Prior empirical studies examine (1) how users react to forward-looking estimates and (2) how managers derive the estimates. With respect to (1), many studies have assessed whether forward-looking estimates are relevant to users' decisions by examining the association between recognized or disclosed fair value figures and equity prices (e.g., Barth et al. 1996; Khurana and Kim 2003; Song et al. 2010). With respect to (2), some studies find that giving managers discretion in making estimates leads to less reliability. Hanley, Jagolinzer, and Nikolova (2018) find evidence that fair values are more inflated when managers use level 3 (unobservable) inputs than when they use level 2 (observable) inputs. Donovan et al. (2023) find that creditors are less likely to use balance sheet-based debt covenants when estimates of pension liabilities are disclosed than when they are recognized on the balance sheet. DeFond, Hu, Hung, and Li (2020) find that fair value estimates mandated through IFRS reduce the usefulness of earnings as a tool to evaluate management performance. While these papers focus on important costs and benefits of using forward-looking estimates, we point to a cost that, to the best of our knowledge, has not been considered in the literature so far—a reduction in managerial learning.

2.2. Managerial Learning

A growing empirical literature documents that information production by a large number of diverse equity investors can complement managers' information set (Goldstein 2023). This literature argues that investors profit by acquiring and trading on information. Consequently, the decentralized, private information of a large number of people and institutions that participate in financial markets is aggregated and incorporated into stock prices (Hayek 1945). A manager facing information collection and processing costs can benefit from this information by considering her firm's stock price in her decision making (Dye and Sridhar 2002). This is particularly true for corporate actions whose future implications are difficult or costly to understand. For example, Luo (2005) shows that managers are less likely to pursue M&A transactions to completion when there is a negative market reaction to the announcement of the deal. Chen et al. (2007) show that capital expenditure and R&D investment sensitivity to price is heightened for firms with more informed stock prices. Both studies provide evidence consistent with managers learning from their firms' stock prices and incorporating that information into complex investment decisions.

There is also a significant interplay between managerial disclosures and learning from price. With respect to voluntary disclosures, Zuo (2016) shows that managers use the information in prices to revise their forecasts of firm performance, and Jayaraman and Wu (2020) demonstrate that managers use the stock market reaction to their voluntary capital expenditure forecast disclosures to adjust their capital expenditure amounts. With respect to mandatory disclosures, Jayaraman and Wu (2019) and Pinto (2023) find that mandatory disclosure of segment data, executive compensation, and higher lags of audited financial statements and selected financial data reduces informed market participants' trading and firms' investment-Q sensitivity. The conclusion drawn by this line of research is that equity prices affect managerial investment and disclosure by providing information incremental to managers' internal information set. Notably, however, these studies focus exclusively on the investment decisions of industrial firms (e.g., M&A, capital expenditures, and R&D). One contribution of our study is to extend the analysis to banks, the most common providers of capital to finance these investment decisions.

Our work is related to a contemporaneous working paper outside of the banking setting by Fan, Jia, and Wang (2024). Fan et al. (2024) show that a rule exempting forward-looking disclosures increases Q-investment sensitivity for mining companies in Canada. Our study differs from theirs along several dimensions. First, our sample includes US banks, while Fan et al. (2024) use a small sample of Canadian mining firms (266 observations). While it is difficult to generalize the findings of either study to other settings, US banks are a pillar of global capital formation and therefore are likely more important for the world economy than Canadian mining firms. Second, our setting leverages a standard change that *mandates* banks to *recognize* forward-looking estimates inside the financial statements. In contrast, Fan et al. (2024) use an exemption to a standard that allows some mining firms to *voluntarily* deviate from established practice by not *disclosing* forward-looking estimates outside the financial statements. It is more difficult to draw causal inferences from voluntary disclosure changes than from mandatory ones. Unlike mandatory disclosure, voluntary disclosure is a choice that might be driven by unobservables for which researchers cannot control (Leuz and Wysocki 2016). Because recognized amounts are presented more prominently than disclosed amounts, preparers and users likely invest less in preparing and understanding disclosed amounts than they do in preparing and understanding recognized amounts (Schipper 2007; Müller et al. 2015; Donovan et al. 2023). Overall, we argue that our paper presents unique insights on how the recognition of forward-looking estimates affects learning.

2.3. Allowance for Loan Losses Accounting and Predictions

Before ASU 2016-13, banks were required to account for their loans by applying the incurred credit loss (ICL) model. The ICL model required banks to state their loans at the historical transaction amount reduced by an allowance for credit losses, which was established whenever a credit loss became "probable" and "reasonably estimable."[14] Although it was predominantly backward-looking, the loan loss allowance amount under ICL was the most economically significant estimate on most banks' financial statements (Beatty, Liao, and Zhang 2019). It likely influenced bank lending because characteristics of the accounting information system (e.g., compliance costs) affect lending decisions (Ege, Nicoletti, and Stuber 2023).

The ICL model incentivized bank managers to employ the information contained in their banks' stock prices in their lending decisions in at least two ways. First, since banks' financial accounting systems made limited use of forward-looking information under the ICL model, bank managers needed to inform their lending decisions through information sources other than financial accounting systems. Stock prices constitute an especially potent incremental information source because managers infer mainly news about macroeconomic conditions from them (Goldstein et al. 2023),[15] and macroeconomic conditions are a key determinant of banks' lending

[14] Since 1991, banks have disclosed fair value estimates for loans they intend to hold to maturity in the footnotes of the financial statements. In theory, these fair value estimates should reflect expected credit losses. However, Cantrell, McInnis, and Yust (2014) show that the disclosed fair value estimates have worse predictive power for future (i.e., expected) credit losses than historical cost figures. Moreover, the extent to which banks were required to change their information systems, improve processing capability, and invest in expertise is evidence that expected credit losses were unlikely to be incorporated into these disclosed fair value estimates (Kim et al. 2023). Overall, these patterns are consistent with prior literature that shows that disclosed accounting information is not as reliable as recognized accounting information (e.g., Bratten, Choudhary, and Schipper 2013; Müller et al. 2015; Donovan et al. 2023).

[15] Specifically, in their 2019 survey, Goldstein et al. (2023) find that 72.4% of bank managers claim to learn from their own banks' stock prices and that 88.9% of these banks learn predominantly about the state of the macroeconomy. One might wonder why managers rely on stock prices rather than publicly available statistics to learn about the macroeconomy. Rational inattention theory provides a potential explanation (Maćkowiak et al. 2023). Managers have limited attention to allocate to the task of deriving the implications of macroeconomic statistics for their firms. Consequently, managers may not pay attention to such statistics (Coibion et al. 2018) and rely on simple heuristics such as stock prices instead.

performance (Mian and Sufi 2010; Khan and Ozel 2016).[16] Second, the limited availability of forward-looking information in banks' financial reports created incentives for bank investors to accumulate and trade on their own estimates of future expected loan losses and thereby increase the degree to which banks' stock prices carry this information. Consistent with this, Wheeler (2021) finds that the stock market prices predicted future credit losses incrementally to the allowance for loan losses during the ICL period.[17]

ASU 2016-13 (ASC 326) and the CECL model became effective in fiscal year 2023 (2020) for small banks (all other banks).[18] CECL eliminates the "probable" criterion and instead requires banks to recognize expected credit losses based on "reasonable and supportable forecasts that affect the collectability of the reported amount" over the entire period the loan will be outstanding (FASB 2016). Given the long horizon of typical bank loans, CECL thus forces banks to consider a significantly larger amount of forward-looking information in developing the allowance for credit losses than ICL. Around the adoption of the standard, the American Banking Association underscored the magnitude of the accounting change for banks' financial reporting and lending, stating that "[t]he Financial Accounting Standards Board's Current Expected Credit Loss

[16] Prior literature finds that macroeconomic fluctuations explain 60-80% of the variation in firms' performance (Brown and Ball 1967; Ball, Sadka, and Sadka 2009). Subsequent studies examine how various macroeconomic developments affect firms' performance. See Ball et al. (2009), Carabias (2018), Jackson, Plumlee, and Rountree (2018), Binz (2022), Binz, Joos, and Kubic (2023d), Binz, Mayew, and Nallareddy (2022), Binz, Ferracuti, and Joos (2023a), Binz et al. (2023b), and Binz, Graham, and Kubic (2023c).

[17] Corroborating this inference, Beatty and Liao (2021) and Lu and Nikolaev (2022) find that analysts' loan loss provision forecasts and empirical loan loss prediction models predict future credit losses even after controlling for ICL provisions.

[18] SEC regulations define a bank as a smaller reporting company if "(1) it has public float of less than $250 million or (2) it has less than $100 million in annual revenues and (a) no public float or (b) public float of less than $700 million." In the initial draft of ASU 2016-13, the FASB set the adoption date to 2021 for small banks and to 2020 for all other banks. In November 2019, the FASB issued an update, ASU 2019-10, and deferred the adoption date of ASU 2016-13 for smaller reporting companies, non-SEC filers, and all other companies to annual and interim periods beginning after December 15, 2022. In March 2020, the US president signed the Coronavirus Aid, Relief, and Economic Security (CARES) Act, which allowed insured depository institutions and credit unions under the supervision of the National Credit Union Administration to postpone their adoption of ASU 2016-13 until the earlier of (1) December 31, 2020, or (2) the end of the national emergency. In December 2022, the Consolidated Appropriations Act changed the CARES Act deadline from December 31, 2020 to December 31, 2022.

impairment standard […] poses significant compliance and operational challenges for banks […] [and] the most sweeping change to bank accounting ever."[19]

Appendix B Panels A and B illustrate the effects of CECL by showing excerpts of JP Morgan's allowance for loan losses footnote under ICL and after CECL adoption. Under ICL, JP Morgan based its allowance estimates on incurred events. After the firm adopted CECL in 2020, the emphasis shifted towards forward-looking estimates, in particular future changes in macroeconomic conditions. Under ICL, estimates were usually final as they were based on events that had already been realized, but under CECL, "[s]ubsequent evaluations of credit exposures, considering the macroeconomic conditions, forecasts and other factors then prevailing, may result in significant changes in the allowance for credit losses in future periods." Panel C presents JP Morgan's discussion of what drove the changes in the allowance for credit losses in 2020. Highlighting the forward-looking nature of CECL disclosures, the authors cite a "deterioration in and uncertainty around the *future* macroeconomic environment" as the main reason. They also provide data on the central assumptions underlying their estimates, i.e., the future developments of the US unemployment rate and GDP growth, and state that changes in these assumptions will directly affect their allowance for loan losses estimate.

We posit that CECL affects how banks learn about expected credit losses from price in two ways. First, CECL requires banks to modify their information collection and processing systems to incorporate more forward-looking information (Kim et al. 2023).[20] These new systems increase the amount of information managers derive from internal and external sources and thereby reduce

[19] See https://www.aba.com/advocacy/our-issues/cecl-implementation-challenges.
[20] In a recent survey, S&P asked banks about CECL implementation and found that CECL implementation cost them "millions of dollars" and required them to hire employees with expertise in credit modeling. Banks did not voluntarily adopt the information systems CECL requires before they were mandated to, which suggests that in the absence of regulation, the cost of these systems outweighs their benefits. Consistent with this conjecture, Ferracuti (2022) finds that managers resort to investing in internal information systems only when market prices become less informative.

managers' reliance on alternative sources, such as their banks' stock prices. Second, CECL reduces investors' incentives to collect and trade on expected loan loss information by forcing managers to recognize expected loan loss estimates. Specifically, managers' recognition of expected loan losses estimates decreases investors' net payoff of forecasting future credit losses privately. It does so either by reducing the information advantage investors could obtain by privately collecting expected loan losses information or by increasing investors' cost of collecting expected loan losses information that would provide them with an information advantage (if the cost of privately collecting incrementally informative information increases in the amount of information that is publicly available). The resulting reduction in information-based trading reduces the extent to which banks' stock prices reveal decision-relevant information to managers and thereby reduces managers' reliance on stock prices when making lending decisions (Gao and Liang 2013).[21] Consistent with this line of reasoning, Bonsall et al. (2022) find that CECL reduces the coverage, forecast accuracy, and agreement of bank analysts. Hence, we predict that CECL adoption reduces bank managers' learning from stock price.

The most direct alternative to the CECL setting is banks' IFRS 9 adoption in other countries than the US. We believe that the CECL setting suits our research question of whether forward-looking estimates deter managerial learning from stock prices better than the IFRS 9 setting for two reasons. First, in contrast to CECL which requires banks to recognize expected credit losses over the lifetime of the loan, IFRS 9 requires banks to recognize expected credit losses over the subsequent year only (IFRS Foundation 2024, Section 5.5).[22] As a result, CECL banks must make

[21] This logic is especially sound for CECL. As illustrated in Appendix B, CECL forces banks to forecast macroeconomic conditions. However, firms do not have a competitive advantage over outsiders when deriving macroeconomic forecasts (Hutton et al. 2012; Vidinova 2024). Indeed, most firms state that they do learn from their own stock price and that this learning is mainly about macroeconomic developments (Goldstein et al. 2023).
[22] Exceptions are loans whose credit risk has increased since their inception. For such loans, IFRS 9 also requires banks to recognize expected credit losses over the loan's lifetime (IFRS Foundation 2024, para. 5.5.3).

more significant forward-looking estimates than IFRS 9 banks. Second, many IFRS 9 banks were required to publicly disclose expected credit losses for regulatory purposes even before IFRS 9's effective date on January 1st, 2018 (Novotny-Farkas 2016). In contrast, US banks were not required to make such disclosures publicly, but only privately to regulators as part of stress testing (ESRB 2019; US Fed 2024). Thus, market participants already had access to some form of banks' expected credit loss estimates before IFRS 9 but not before CECL adoption. As a result, the CECL setting constitutes a cleaner increase in forward-looking estimates than the IFRS 9 setting.

3. Research Design

We estimate CECL's effect on bank managers' learning from their firms' stock prices by employing a modification of the lending prediction model in Beatty and Liao (2011):

$$\begin{aligned}\Delta Loan_{it+1} = {} & \beta_1\, Tobin\text{'}s\ Q_{it} + \beta_2\, Treat_i \times Tobin\text{'}s\ Q_{it} + \beta_3\, Post_t \times Tobin\text{'}s\ Q_{it} \\ & + \beta_4\, Treat_i \times Post_t \times Tobin\text{'}s\ Q_{it} + Controls + \Gamma_i + \Phi_t + \varepsilon_{it}.\end{aligned} \tag{1}$$

$\Delta Loan_{it+1}$ denotes the change in loans scaled by total assets for bank i in quarter $t+1$.[23] Following Begenau et al. (2020), who develop and validate measures of Tobin's Q for the banking industry, we define *Tobin's Q* as the market value of equity divided by the book value of equity.[24] *Post* is an indicator for year-quarters following 2020Q1, the quarter including ASU 2016-13's effective date for large banks. ASU 2016-13 allowed small banks to defer adoption until 2023Q1.[25] Taking advantage of this institutional fact, we define our treatment group as large banks and our control

[23] Following Chen et al. (2023) and Kim et al. (2023), we exclude Paycheck Protection Program (PPP) loans across all variable computations.
[24] One concern is that CECL might help investors to determine banks' future loan growth more accurately, which would change banks' lending-Q sensitivity even in the absence of managerial learning. In untabulated tests, we examine this possibility by regressing loan growth two to four years ahead on Tobin's Q. We find that Tobin's Q is already significantly related to future loan growth before CECL and, importantly, that these relations do not significantly change because of CECL.
[25] The SEC defines small banks as banks with either (1) a public float (the number of the company's common shares held by non-affiliates multiplied by the market price of these shares) of less than $250 million or (2) annual revenues of less than $100 million and either (2.a) no public float or (2.b) a public float of less than $700 million. It defines all other banks as large banks.

group as small banks. Thus, *Treat* is an indicator that takes a value of one for large banks and a value of zero for small banks. Figure 1 Panel A illustrates our identification strategy.

The control variables include the natural logarithm of market value in US dollars (*Log(Market Cap)*), total deposits scaled by total loans (*Deposits*), the standard deviation of the bank's daily stock returns over the quarter (*StD(Returns)*), change in the tier 1 capital ratio as defined in Basel III (the sum of the bank's common shares and stock surplus, retained earnings, other comprehensive income, qualifying minority interest, and regulatory adjustments scaled by its total risk-weighted assets) (Δ*Tier 1 Capital Ratio*), and the stand-alone variables and the interaction term between the tier 1 capital ratio (*Tier 1 Capital Ratio*) and a recession indicator (*Recession*) (Beatty and Liao 2011). We also control for time-invariant bank-specific factors and the dynamic evolution of the macroeconomic environment (which is especially important since our sample features the outbreak of the COVID-19 pandemic) by including bank (Γ) and year-quarter (Φ) fixed effects. We list all variable definitions in Appendix A.[26]

If bank managers learn from their banks' stock prices, we expect a positive relation between future lending and Tobin's Q (Tobin 1969; Chen et al. 2007). Further, if the use of forward-looking estimates mandated by ASU 2016-13 disincentivizes investors to collect and trade based on information about banks' future lending performance and thereby reduces the usefulness of stock prices for bank managers' lending decisions, we expect a negative coefficient on the triple interaction term among *Treat*, *Post*, and *Tobin's Q*.

[26] In addition to including year-quarter fixed effects, we take four approaches to addressing the concern that the COVID-19 outbreak explains our results. First, Table 5 and Table 8 Panel A estimate the effect of CECL on large US banks relative to small US and large international banks, respectively. Thus, for the COVID-19 outbreak to explain our results, it must affect these banks differentially *in the same direction as CECL*. Second, Table 8 Panel B estimates the effect of CECL on small US banks relative to large US banks following small US banks' delayed CECL adoption in 2023Q1, years after the COVID-19 outbreak. Third, we drop the quarter with the highest uncertainty surrounding the COVID-19 outbreak (2020Q2). Fourth, we remove all US PPP lending from our lending change variable measurement, since PPP lending was larger in magnitude for non-CECL adopting US banks (Ballew et al. 2022). Our results are robust to all of these changes.

4. Data

We obtain our sample of large and small public US banks from Compustat Bank Fundamentals, market capitalization information from CRSP, and bank-specific information from FR Y-9C reports. We use Compustat Bank Fundamentals rather than other data sources because it provides full coverage of basic financial information for public banks. We obtain the date on which a given bank adopted ASU 2016-13 from Compustat Bank Fundamentals; if it is missing, we hand collect it from banks' 10-Ks. We collect data on CECL's adoption impact on banks' balance sheets and income statements from FR Y-9C reports, and, if missing, from banks' 10-Ks.

Table 1 Panel A shows the CECL adoption timetable for public banks. We restrict our sample to five quarters before and after the adoption quarter 2020Q1, for a total of 11 quarters between 2018Q4 and 2021Q2. Even though banks were allowed to delay their adoption of CECL, the majority opted for on-time adoption at the original adoption date. Specifically, 76% (= 141/[141 + 44]) of large banks adopted CECL in 2020Q1. For consistency, we exclude the remaining 44 large banks that adopted after 2020Q1 (i.e., late adopters) from our sample. One might argue that these banks' decision to defer is a function of a range of unobservable factors, such as their competitive position within the industry or the amount of available internal resources to support CECL adoption. Hence, one should be cautious in generalizing our findings to these late adopters. Our final sample includes 2,909 bank-quarters, representing 282 banks. Table 1 Panel B shows our number of treatment and control observations by year-quarter over our sample period. The sample is close to balanced across years and across the treatment and control groups.

Table 2 presents the descriptive statistics for all variables other than *Post* and *Treat*. Banks' lending grows by 1.4% on average, although there is substantial variation with a standard deviation of 3.9%. The average (1.123) and median (1.063) Tobin's Q are close to but higher than one. On average, banks maintain a tier 1 capital ratio of 12.7%, have a market capitalization of $653 million (= exp[6.482]), experience a 2.6% stock return standard deviation, and generally have more deposits than loans. 27.5% of our observations fall in a recession. Table 3 presents the correlation matrix. Growth in lending is positively correlated with Tobin's Q, consistent with bank managers adjusting their lending decisions to changes in their banks' stock prices. Larger banks, banks with a higher tier 1 capital ratio, and banks with more deposits experience smaller loan growth.

Table 4 shows pre-period univariate comparisons for the treatment and control groups over the pre-CECL period (2018Q4 to 2019Q4). As expected, because size differences define the two groups, banks in the treatment group are on average 12.71 times (= exp[7.734 – 5.192]) larger than banks in the control group. Treatment and control banks also differ significantly across most of the other control variables. In addition to controlling for these observables, we attempt to remedy observable and unobservable differences by employing an alternative entropy-balanced control group of EU and UK banks. We discuss these supplemental tests in Section 5.4.

5. Results

5.1. Lending-Q Sensitivity

Table 5 shows the results of estimating Equation (1). We standardize all continuous variables to facilitate interpretation. We cluster standard errors at the firm level and gradually expand the covariates in the model from Column (1) to (3). Column (1) establishes the baseline result of lending-Q sensitivity. Tobin's Q exhibits a significantly positive partial correlation with future lending, suggesting that bank managers adjust their lending decisions to movements in their banks' stock prices. In terms of economic magnitude, a one standard-deviation change in Tobin's Q is associated with a 0.634 standard-deviation change in future lending in the same direction. Column (2) includes the interaction term of *Treat* and *Tobin's Q*. The interaction term's slope coefficient is not significantly different from zero, suggesting that managers' reliance on banks' stock prices does not systematically differ between treatment and control banks.

Most importantly for our study, Column (3) further interacts *Treat* and *Tobin's Q* with *Post* and thereby estimates how CECL affects treatment bank managers' lending-Q sensitivity differently from that of control bank managers. The triple interaction term is significantly negative, suggesting that CECL reduces managers' reliance on their banks' stock prices. In terms of economic magnitude, the estimates suggest that CECL reduces managers' lending-Q sensitivity by 0.245 standard deviations, or 32.07% (= 0.245/0.764) of *Tobin's Q*'s main effect. We also find that both treatment and control banks experience an increase in lending-Q sensitivity after CECL adoption, indicating that stock prices became more useful to bank managers. However, we are cautious in interpreting this coefficient since our sample period includes times of macroeconomic turmoil, specifically the outbreak of COVID-19. Such turmoil could change managers' reliance on stock prices through channels other than CECL and invalidate the interpretation of time-series changes.

Figure 2 helps us understand whether there is support for the parallel trends assumption underlying our difference-in-differences design. We estimate Equation (1) after replacing *Post* with indicators for the year-quarters included in our sample, interacting them individually with *Treat* and *Tobin's Q*, and plotting the slope coefficients of the resulting triple interaction terms (Christensen, Hail, and Leuz 2016). We use 2019Q4 as the base quarter. In support of our parallel trends assumption, we do not find a clear trend in the difference between treatment and control banks' lending-Q sensitivity during the pre-CECL period. However, lending-Q sensitivity significantly falls for treatment banks relative to control banks one quarter after CECL adoption. This difference remains negative thereafter.

5.2. Different Loan Types

Our findings suggest that CECL causes managers to learn less from their banks' stock prices. One explanation is that CECL reduces investors' collection of and trading based on information that is useful to bank managers (Gao and Liang 2013). We test this mechanism by examining how CECL differentially affects banks' lending-Q sensitivity for different loan types for which investors likely can collect information incremental to that of the bank manager. Specifically, we test how CECL differentially affects banks' lending-Q sensitivity for long-term homogenous loans, short-term homogenous loans, and heterogenous loans.

Heterogenous loans are largely composed of commercial and industrial loans. They tend to be managed at the individual loan level and issued with tailored contract terms that are renegotiable and backed by collateral. In contrast, homogenous loans are largely composed of consumer and real estate loans. These loans tend to be managed at the portfolio level and issued with standardized terms that are determined by current macroeconomic conditions (such as the unemployment rate and GDP growth). While managers tend to have an information advantage over informed outsiders when it comes to firm-level conditions, outsiders tend to have an information advantage over managers when it comes to macroeconomic conditions (Hutton et al. 2012; Vidinova 2024). Thus, we expect managers' learning from prices and CECL's impediment to it to be weaker for heterogenous loans for which bankers can learn less from the market.

Further, Ryan (2019) argues that CECL's effects will be more pronounced for long-run than for short-run homogenous loans. Even under ICL, banks already recorded an allowance for expected credit losses over the next twelve months at the inception of homogenous loans. As a result, CECL does not significantly change the accounting representation of short-term homogenous loans with an expected maturity of approximately twelve months or less. Thus, we expect managers' learning from price and CECL's impediment of it to be weaker for short-term homogenous loans than for long-term ones.

Table 6 Panels A to C report the results of estimating Equation (1) after replacing Δ*Loan*$_{t+1}$ with Δ*Long-Term Homogenous Loans*$_{t+1}$ (which we measure as real estate loans), Δ*Short-Term Homogenous Loans*$_{t+1}$ (which we measure as consumer loans), and Δ*Heterogenous Loans*$_{t+1}$ (which we measure as commercial and industrial loans) as the dependent variable. As expected, we find that the effect concentrates in long-term homogenous loans rather than short-term homogenous loans or heterogenous loans. While CECL's effect on the lending-Q sensitivity is significant for long-term homogenous loans (Panel A), the effect turns insignificant for short-term homogenous loans (Panel B) and heterogenous loans (Panel C). In terms of economic magnitude, we find that the lending-Q sensitivity of long-term homogenous loans falls by 0.361 standard deviations (or 44.35% [= 0.361/0.814] of *Tobin's* Q's main effect) more for treatment banks than for control banks following CECL. The fall in lending-Q sensitivity is significantly smaller for long-term homogenous loans than for short-term homogenous loans (p = 0.000) and heterogenous loans (p = 0.055).

Collectively, these tests suggest that (1) CECL's negative effect on managerial learning is stronger when bank managers have more potential to learn from their banks' stock prices, and (2) decentralized information collection through investors is the underlying mechanism.

5.3. Lending Efficiency and Riskiness

Our findings so far suggest that CECL reduces managers' reliance on their banks' stock prices when they make lending decisions because it disincentivizes investors to privately collect and trade on lending-related information. However, it remains unclear whether this change in lending practices is efficient, since it can be driven by bank managers relying less on stock prices as an information source because either (1) banks' internal information system quality increases, which would suggest an increase in efficiency (Kim et al. 2023; Gelsomin 2024) or because (2) investors collect and trade less on information pertaining future loan performance (Gao and Liang 2013). To address this, we examine how CECL affects different efficiency outcomes by estimating the following regression separately for firms that experience a decrease and firms that experience an increase in lending-Q sensitivity (which we estimate via firm-level regressions) around CECL:

$$ROA_{it+1} = \beta_1 \, Treat_i \times Post_t + Controls + \Gamma_i + \Phi_t + \varepsilon_{it}. \tag{2}$$

ROA denotes return on assets. One issue with the calculation of return on assets and its components in our setting is that the switch from ICL to CECL leads to large day-one impacts on net income and total assets. To address this concern, we compute *ROA* by measuring its numerator as net income plus after-tax loan loss provisions (to account for temporary differences between CECL and non-CECL banks) and measuring its denominator as total assets plus the loan loss allowance (to account for permanent differences between CECL and non-CECL banks) plus the change in the loan loss allowance in the adoption year (to account for the day-one impact). Following Hou, Dijk, and Zhang (2012), we control for the natural logarithm of total Assets (*Log (Assets)*), dividends scaled by total assets (*Dividend*), an indicator that the firm declares dividends (*Dividend Payer*), an indicator that the firm makes a loss (*Loss*), and accruals scaled by total assets (*Accruals*). If CECL increases (decreases) the efficiency of bank managers' lending decisions, we expect the slope coefficient of the interaction term to be positive (negative).

Table 7 Columns (1) and (2) show the results. Consistent with CECL reducing banks' lending efficiency, we find that bank profitability decreases for treatment relative to control firms following CECL adoption more when banks experience a decrease in lending-Q sensitivity. In terms of economic magnitude, bank profitability falls by 0.337 (0.056) standard deviations more for treatment than for control banks when banks also experience a decrease (an increase) in lending-Q sensitivity. While this effect magnitude may seem large at first glance, given the small standard deviation in bank profitability of 0.1%, this amounts to a 0.0337% (= 0.337 × 0.1%) reduction in return on assets. The last rows of both panels (*Decrease – Increase*) test and confirm that the differences in coefficients across Columns (1) and (2) are statistically significant (p = 0.000) when we use a 1,000-repetition bootstrap procedure.

Table 7 Columns (3) to (6) examine the sources of this change in profitability by decomposing *ROA* into adjusted net income divided by total interest income (*Profit Margin*) and total interest income divided by adjusted total assets (*Asset Turnover*). We interpret *Profit Margin* as the bank's ability to maximize interest received on issued loans and *Asset Turnover* as the bank's ability to efficiently identify lending opportunities. The results suggest that the fall in profitability is caused by a change in efficiently identifying lending opportunities that outweighs an improvement in the bank's ability to profitably set interest rates on loans it issues. While CECL's effect on profit margins is insignificant regardless of whether banks experience a decrease [Column (3)] or an increase [Column (4)] in lending-Q sensitivity, its effect on asset turnover is significantly negative for banks that experience a decrease in lending-Q sensitivity [Column (5)], but insignificant for banks that experience an increase in lending-Q sensitivity [Column (6)]. These results suggest that CECL's negative effect on bank managers' learning from stock prices reduces banks' lending efficiency, but not their pricing power.

Lastly, an alternative explanation for the decrease in profitability is that the accounting procedures mandated by CECL reduce bank managers' willingness to issue riskier loans with higher interest rates. Prior evidence on whether this is indeed the case is mixed. On the one hand, Granja and Nagel (2023) find no evidence that CECL induces banks to either change interest rates or ration credit. On the other hand, Basu et al. (2023) find that CECL induces banks to reduce loan amounts and to offer stricter financing terms. In Table 7 Columns (7) and (8), we examine whether CECL affected the lending behavior of our sample banks by replacing return on assets with the banks' average interest rate charged on loans (*Interest Rate*). Consistent with Granja and Nagel (2023) but inconsistent with the notion that CECL induced banks to change the riskiness of their loan portfolio, the interaction terms' slope coefficient is insignificant across all models.

In total, the results suggest that CECL reduces banks' lending efficiency because the fall in bank managers' learning from stock prices decreases banks' ability to pursue lending opportunities more than the CECL-related investments in banks' financial reporting systems increase banks' ability to assess credit risk. We argue that this loss in efficiency is at least partially attributable to the reduction in managers' ability to learn from the stock market.

5.4. Alternative Control Group

A limitation of our study is that we rely on small banks that adopt CECL three years later than large banks as our control group. To overcome the concern that these small public banks are intrinsically different from their large peers, we use banks that previously adopted IFRS 9 as an alternative control group.[27] We include European and UK banks because they operate in institutionally similar capital markets and have comparable sizes and lending portfolios to large US banks. To account for remaining differences between our treatment banks and IFRS 9 banks, we entropy balance the IFRS 9 banks to our treatment banks on all control variables. Figure 1 Panel B illustrates this alternative research design.

[27] One important difference between ASU 2016-13 and IFRS 9 is that IFRS 9 requires a credit loss forecast only over the upcoming twelve months. However, expected credit loss accounting of the EU and UK banks that adopt IFRS 9 does not change over our sample period. Thus, these banks are a reasonable control group. Several papers study the effects of IFRS 9 on other variables than learning. See, e.g., Novotny-Farkas (2016), Bholat, Lastra, Markose, Miglionico, and Sen (2018), Seitz, Dinh, and Rathgeber (2018), Kund and Rugilo (2019), Ertan (2021), López-Espinosa, Ormazabal, and Sakasai (2021), Witzany and Pastiranová (2021), Oberson (2021), Bischof, Haselmann, Kohl, and Schlueter (2022), Dong and Oberson (2022), and Kalista and Novotny-Farkas (2023).

Table 8 Panel A replicates Table 5 after employing this entropy-balanced sample of IFRS 9 banks as an alternative control group. We continue to document a significantly positive relation between Tobin's Q and lending, and we still find that CECL adoption mitigates this relation.

5.5. Alternative Treatment Group

In our main tests, we find that large banks' lending-Q sensitivity decreases following their adoption of CECL in 2020Q1 relative to that of small banks that are allowed to delay adoption until 2023Q1. While these findings are consistent with our theory, our theory also predicts that small banks' lending-Q sensitivity will decrease relative to that of large banks following their adoption of CECL in 2023Q1. Figure 1 Panel C illustrates this alternative research design.

To test whether CECL's negative effects on lending-Q sensitivity are also present around 2023Q1, we re-estimate Equation (1) after re-classifying *Post* as an indicator for year-quarters following 2023Q1 and *Treat* as an indicator that takes a value of one for small banks and a value of zero for large banks. The panel includes 2022Q1 to 2022Q4 as the pre period and 2023Q1 to 2023Q2 as the post period, as 2023Q2 is the last quarter with data available at the time of writing.

Table 8 Panel B presents the results. As in Table 5, we document a significantly positive relation between Tobin's Q and lending and find that CECL adoption weakens this relation. These results suggest that the findings in Table 5 not only pertain to large US banks but also generalize to their smaller counterparts that adopted CECL later.

5.6. Additional Robustness Tests

Table 9 conducts three additional analyses to verify the robustness of our main results. First, CECL leads to a difference in equity calculation between adopting and non-adopting banks, with adopting banks incorporating future loan loss provisions in the equity calculation. To circumvent the mechanical difference in Tobin's Q, in Column (1), we add back CECL's day-one effect and the allowance for loan loss to book value equity to calculate an adjusted Tobin's Q in the post-CECL period (*Tobin's Q adj.*). Second, in Column (2), we follow Pinto (2023) and replace Tobin's Q with the natural logarithm of market value of equity scaled by book value of assets (*log(Market Cap/Assets)*). Third, in Column (3), we use total loans instead of total assets as the scalar to compute our loan growth, the dependent variable. Our results are robust across all tests.

6. Conclusion

We examine how the use of forward-looking estimates affects managerial learning from stock prices using the adoption of CECL for banks as a setting. Our study is novel in two respects. First, we extend the managerial learning literature, which has focused exclusively on industrial firms, to banks. We find evidence that banks' lending is indeed sensitive to the information contained in stock prices. This suggests that investors' information, which is incorporated into stock prices through the trading process, helps bank managers in their lending decisions. Second, we find that the use of forward-looking estimates mandated by CECL reduces managers' lending sensitivity to their banks' stock prices. This suggests that the use of forward-looking estimates and the disclosures accompanying them reduce the net benefit for investors to collect and trade based on lending-relevant information, rendering stock prices less useful decision-making tools for bank managers. The results are pronounced for types of lending decisions for which bank managers have a larger potential to learn from investors. They are also robust to employing alternative control groups, treatment groups, and measurement approaches. Finally, we find evidence that the reduction in learning appears to hurt bank lending efficiency, which suggests that the use of forward-looking estimates has some implications for the real efficiency of banks.

We acknowledge that the inferences we have drawn from the adoption of ASU 2016-13 may not extend to other standards that mandate different types of forward-looking estimates. However, we believe that our paper is an important step towards expanding our understanding beyond the literature's current emphasis on reliability and relevance. As such, it can inform standard setters about the unintended consequences of ASU 2016-13.

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Appendix A. Variable Definitions

Variable	Source	Description
Δ*Loan*	Compustat	Change from the beginning to the end of the quarter in loans (lgq) scaled by total assets (atq) at the beginning of the quarter.
Δ*Loan$_{loan}$*	Compustat	Change from the beginning to the end of the quarter in loans (lgq) scaled by total loans (lgq) at the beginning of the quarter.
Δ*Tier 1 Capital Ratio*	Compustat	Change from the beginning to the end of the quarter in the Tier 1 Capital Ratio (capr1q) defined below.
Accruals	Compustat	Income before extraordinary items (ibq) minus net cash flow from operating activities (oancfq).
Asset Turnover	Compustat, FR Y-9C	Total interest income (iditq) divided by total assets (atq) adjusted for day 1 impact (BHCKJJ26) and loan loss allowance (rllq) at the beginning of the quarter.
Deposits	Compustat	Total deposits (dptcq) scaled by total loans (lgq).
Dividend	Compustat	Dividends declared (dvcq) scaled by total assets (atq).
Dividend Payer	Compustat	Indicator that a firm declares dividends (dvcq).
Δ*Heterogenous Loans*	Compustat, FR Y-9C	Change from the beginning to the end of the quarter in commercial and industrial loans (BHCK1766) divided by total assets (atq) at the beginning of the quarter.
Δ*Long-Term Homogenous Loans*	Compustat, FR Y-9C	Change from the beginning to the end of the quarter in real estate loans (BHCK1410) divided by total assets (atq) at the beginning of the quarter.
Δ*Short-Term Homogenous Loans*	Compustat, FR Y-9C	Change from the beginning to the end of the quarter in consumer loans (BHCKB538+BHCKB539+BHCKK137+BHCKK207) divided by total assets (atq) at the beginning of the quarter.
Interest Rate	Compustat	Total interest income (iditq) divided by loans (lgq) at the beginning of the quarter.
Log(Assets)	Compustat	Natural logarithm of total assets (atq).
Log(Market Cap)	Compustat, Refinitiv	Natural logarithm of market capitalization (mkvaltq) in US dollars.
Log(Market Cap/Assets)	Compustat	Natural logarithm of market value of equity (mktval) scaled by book value of assets (atq).
Loss	Compustat	Indicator that a firm has a negative income before extraordinary items (ibq).
Post	Compustat	Indicator that the year-quarter is 2020Q1 (2023Q1) or later (in the CECL 2023 adoption test).
PPP	FR Y-9C	Paycheck Protection Program (PPP) loans (BHCKLG27) divided by total loans (atq). We exclude PPP from total assets, total loans, and heterogenous loan calculation in the variables defined above.

Profit Margin	Compustat	Net income (niq) adjusted for after-tax loan loss provisions (pllq) divided by total interest income (iditq). Tax rate is calculated as income tax applicable to current operating incomes (itacoeq) divided by current operating earnings before income tax (coeitq).
Recession	NBER	Indicator of NBER-defined recession period, specifically, 2019 Q4 to 2020 Q2 in our sample period.
ROA	Compustat, FR Y-9C	Net income (niq) adjusted for after-tax loan loss provisions (pllq) divided by total assets (atq) adjusted for day 1 impact (BHCKJJ26) and loan loss allowance (rllq).
StD(Return)	CRSP, Refinitiv	Standard deviation of daily return (RET) of the current quarter.
Tier 1 Capital Ratio	Compustat, 10-Ks	The ratio of a bank's core tier 1 capital—Sum of common shares and stock surplus, retained earnings, other comprehensive income, qualifying minority interest and regulatory adjustments—to its total risk-weighted assets (capr1q).
Tobin's Q	Compustat, CRSP, Refinitiv	Market capitalization (mkvaltq) divided by book value of equity (teqq).
Tobin's Q adj.	Compustat, CRSP	Market value of equity (mkvaltq) divided by adjusted book value equity. We compute adjusted book value of equity as book value equity (teqq) plus CECL's day-one effect (BHCKJJ26) and allowance for loan loss (rclq).
Treat	Compustat, 10-Ks	Indicator that the bank adopted CECL in 2020Q1 (2023Q1).

Appendix B. JP Morgan Credit Loss Allowance Disclosures

Panel A. Under ICL

Note 13 – Allowance for credit losses

JPMorgan Chase's allowance for loan losses represents management's estimate of probable credit losses inherent in the Firm's retained loan portfolio, which consists of the two consumer portfolio segments (primarily scored) and the wholesale portfolio segment (risk-rated). The allowance for loan losses includes a formula-based component, an asset-specific component, and a component related to PCI loans, as described below. Management also estimates an allowance for wholesale and certain consumer lending-related commitments using methodologies similar to those used to estimate the allowance on the underlying loans.

The Firm's policies used to determine its allowance for credit losses are described in the following paragraphs.

Determining the appropriateness of the allowance is complex and requires judgment by management about the effect of matters that are inherently uncertain. Subsequent evaluations of the loan portfolio, in light of the factors then prevailing, may result in significant changes in the allowances for loan losses and lending-related commitments in future periods. At least quarterly, the allowance for credit losses is reviewed by the CRO, the CFO and the Controller of the Firm. As of December 31, 2019, JPMorgan Chase deemed the allowance for credit losses to be appropriate and sufficient to absorb probable credit losses inherent in the portfolio.

Panel B. Under CECL

Note 13 – Allowance for credit losses

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

JPMorgan Chase's allowance for credit losses comprises:

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

The income statement effect of all changes in the allowance for credit losses is recognized in the provision for credit losses. Determining the appropriateness of the allowance for credit losses is complex and requires significant judgment by management about the effect of matters that are inherently uncertain. At least quarterly, the allowance for credit losses is reviewed by the CRO, the CFO and the Controller of the Firm. Subsequent evaluations of credit exposures, considering the macroeconomic conditions, forecasts and other factors then prevailing, may result in significant changes in the allowance for credit losses in future periods.

The Firm's policies used to determine its allowance for loan losses and its allowance for lending-related commitments are described in the following paragraphs. Refer to Note 10 for a description of the policies used to determine the allowance for credit losses on investment securities.

Panel C. Additional CECL Disclosures

Discussion of changes in the allowance during 2020
The increase in the allowance for loan losses and lending-related commitments was primarily driven by an increase in the provision for credit losses, reflecting the deterioration in and uncertainty around the future macroeconomic environment as a result of the impact of the COVID-19 pandemic.

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

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

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

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

	Assumptions at January 1, 2020		
	2Q20	4Q20[b]	2Q21
U.S. unemployment rate[a]	3.7%	3.8%	4.0%
Cumulative change in U.S. real GDP from 12/31/2019	0.9%	1.7%	2.4%

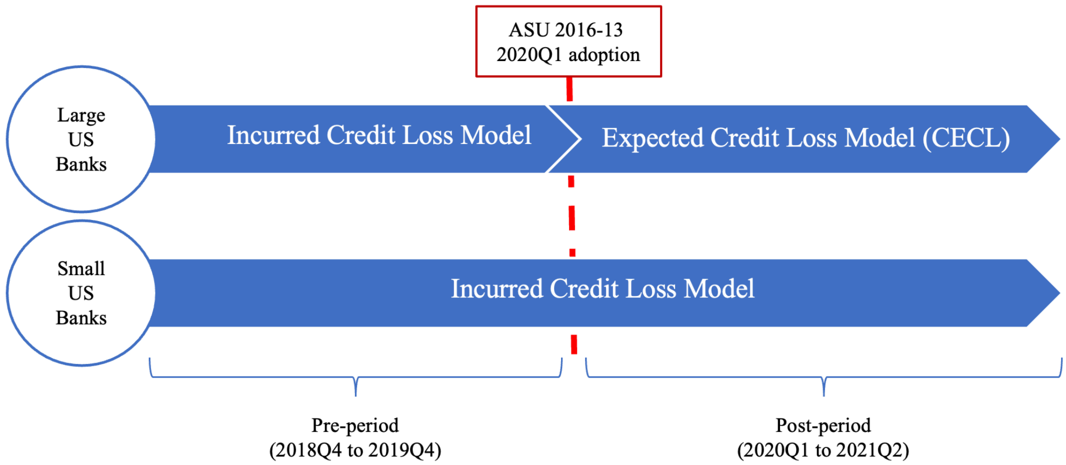
	Assumptions at December 31, 2020		
	2Q21	4Q21	2Q22
U.S. unemployment rate[a]	6.8%	5.7%	5.1%
Cumulative change in U.S. real GDP from 12/31/2019	(1.9)%	0.6%	2.0%

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

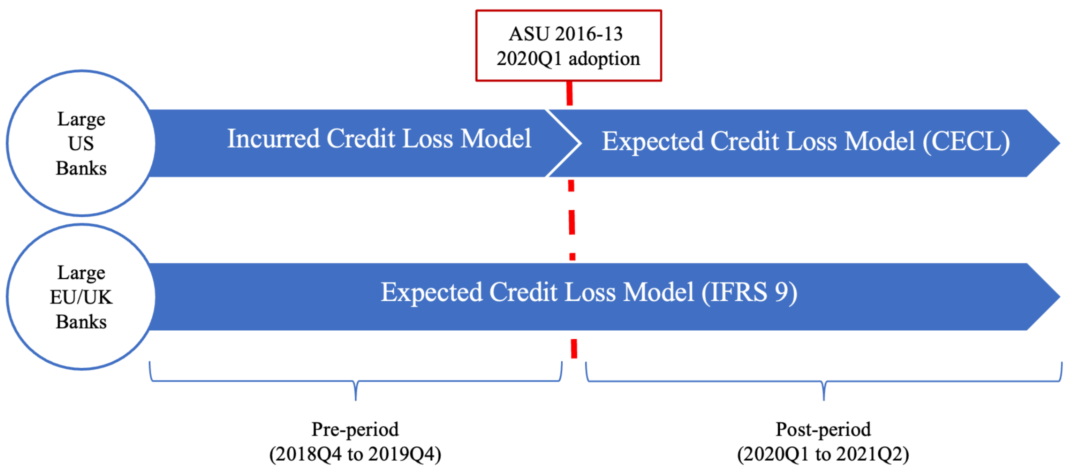
Subsequent changes to this forecast and related estimates will be reflected in the provision for credit losses in future periods.

Figure 1. ASU 2016-13 and Identification Strategy Timeline

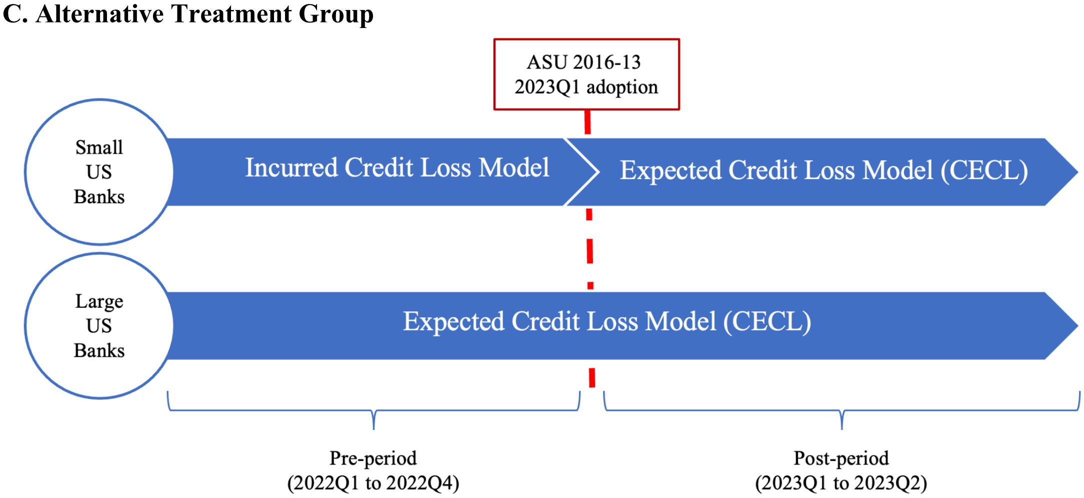
Panel A. Main Tests



Panel B. Alternative Control Group

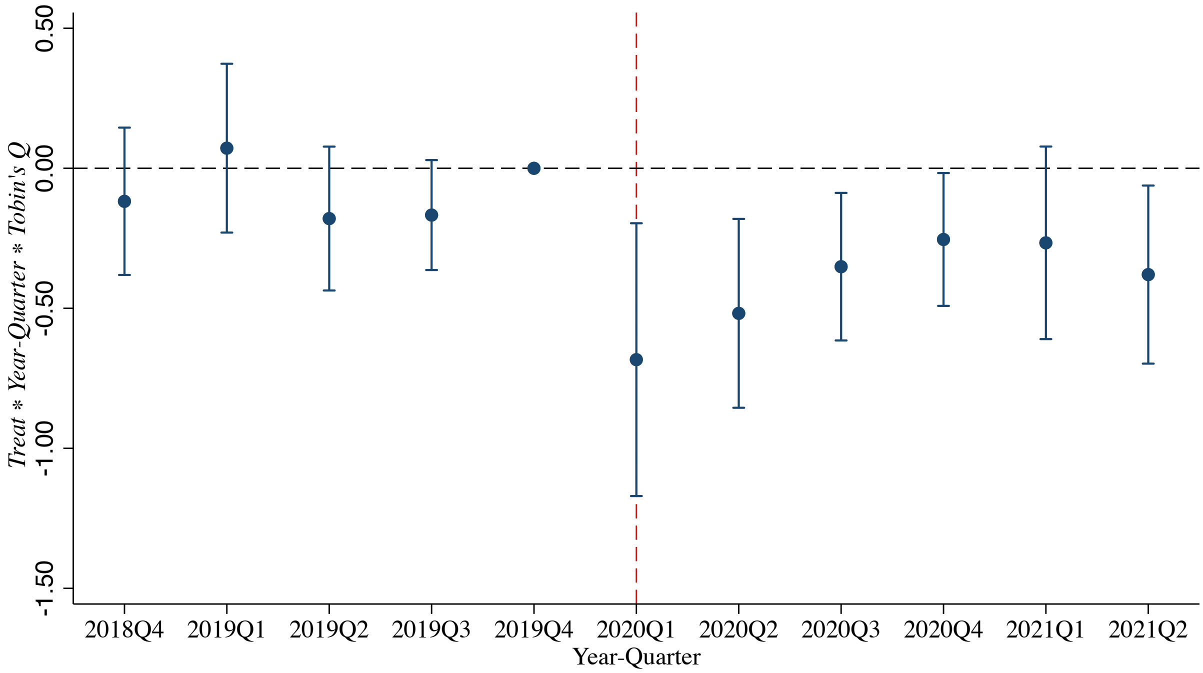


Panel C. Alternative Treatment Group



Panels A, B, and C illustrate the three alternative treatment and control group classifications we employ to examine the effects of ASU 2016-13.

Figure 2. Parallel Trends Test



This figure tests the parallel trends assumption of the difference-in-difference design by regressing banks' future lending growth on an indicator that the bank adopted CECL in 2020Q1 (*Treat*) interacted with Year-Quarter indicators and Tobin's Q. Controls, firm fixed effects, and year-quarter fixed effects are included. Standard errors are clustered at the firm level. This figure displays the slope coefficient and 90% confidence interval for the interaction terms. 2019Q4 constitutes the base quarter. Continuous variables are standardized.

Table 1. CECL Sample Composition

Panel A. CECL Adoption Timetable

	Banks	Observations	% of Total
Adopted on 2020Q1 (Treat)	141	1,537	53%
Adopted on 2020Q3	*4*	-	-
Adopted on 2020Q4	*6*	-	-
Adopted on 2021Q1	*21*	-	-
Adopted on 2022Q1	*12*	-	-
Adopted on 2022Q3	*1*	-	-
Adopted on 2023Q1 or later (Control)	141	1,372	47%
Full Sample	282	2,909	100%

Panel B. CECL Banks vs. CECL Late Adopters

	Treat	*Control*	Total	Event Time
2018Q4	141	125	266	-5
2019Q1	141	127	268	-4
2019Q2	141	128	269	-3
2019Q3	141	132	273	-2
2019Q4	141	134	275	-1
2020Q1	139	125	264	0
2020Q2	139	123	262	1
2020Q3	139	123	262	2
2020Q4	139	122	261	3
2021Q1	138	120	258	4
2021Q2	138	113	251	5
	1,537	1,372	2,909	

This table presents our sample composition. Panel A displays the CECL adoption time of all public banks in the US. We define the banks that adopted CECL in 2020Q1 as the treated group and banks that adopted it in 2023Q1 or later as the control group. Banks that elected the right to delay CECL adoption are excluded from our tests. Panel B displays the panel structure for the difference-in-difference tests.

Table 2. Summary Statistics

	N	Mean	StD	P25	Median	P75
ΔLoan	2,909	0.014	0.039	-0.004	0.006	0.020
Tobin's Q	2,909	1.123	0.404	0.860	1.063	1.302
Tobin's Q adj.	2,909	1.151	0.453	0.871	1.083	1.324
Tier 1 Capital Ratio	2,909	0.127	0.023	0.111	0.122	0.137
Recession	2,909	0.275	0.447	0.000	0.000	1.000
ΔTier 1 Capital Ratio	2,909	0.000	0.006	-0.002	0.001	0.003
Deposits	2,909	1.226	0.483	1.038	1.124	1.267
StD(Return)	2,909	0.026	0.015	0.016	0.021	0.031
PPP	2,909	0.018	0.036	0.000	0.000	0.006
Log(Market Cap)	2,909	6.482	1.694	5.167	6.232	7.611
ΔLong-Term Homogenous Loans	2,503	0.011	0.031	-0.002	0.004	0.013
ΔShort-Term Homogenous Loans	2,503	0.000	0.003	0.000	0.000	0.000
ΔHeterogenous Loans	2,503	0.002	0.004	0.000	0.001	0.003
ROA	2,618	0.003	0.001	0.003	0.003	0.004
Profit Margin	2,618	0.351	0.143	0.276	0.344	0.422
Asset Turnover	2,618	0.009	0.002	0.008	0.009	0.010
Interest Rate	2,618	0.014	0.003	0.012	0.013	0.015
Log(Assets)	2,618	8.785	1.618	7.479	8.609	9.707
Dividends	2,618	0.001	0.001	0.000	0.001	0.001
Accruals	2,618	0.000	0.007	-0.002	-0.001	0.001
log(Market Cap/Asset)	2,909	0.116	0.042	0.086	0.111	0.142
$\Delta Loan_{loan}$	2,909	0.022	0.061	-0.008	0.009	0.030

This table presents summary statistics. All variables are defined in Appendix A. The sample period spans from 2018Q4 to 2021Q2.

Table 3. Correlation Matrix

Variable		1	2	3	4	5	6	7	8	9
ΔLoan	1	1.000	0.200	0.186	-0.036	-0.101	-0.083	-0.147	-0.091	-0.052
Tobin's Q	2	0.094	1.000	0.977	0.248	0.009	0.153	-0.460	-0.116	0.232
Tobin's Q adj.	3	0.087	0.967	1.000	0.232	0.026	0.170	-0.435	-0.053	0.265
Tier 1 Capital Ratio	4	0.002	0.232	0.211	1.000	0.164	0.359	-0.052	0.022	-0.040
ΔTier 1 Capital Ratio	5	-0.065	-0.003	0.010	0.089	1.000	0.082	0.002	0.189	0.037
Deposits	6	-0.055	0.158	0.170	0.269	-0.017	1.000	0.061	0.247	0.182
StD(Return)	7	0.033	-0.359	-0.322	-0.049	-0.055	-0.032	1.000	0.312	-0.113
PPP	8	-0.055	-0.038	0.039	0.007	0.118	0.079	0.189	1.000	0.316
Log(Market Cap)	9	-0.055	0.222	0.254	-0.038	0.022	0.295	-0.124	0.191	1.000

This table presents the correlation matrix for the main sample. Pearson (Spearman) correlations are below (above) the diagonal. Variables are defined in Appendix A.

Table 4. Pre-Period Comparison

	Treat (N = 705)		*Control* (N = 646)		
	Mean	StD	Mean	StD	*Difference*
ΔLoan	0.018	0.042	0.015	0.031	-0.003
Tobin's Q	1.287	0.391	1.226	0.319	-0.062**
Tier 1 Capital Ratio	0.125	0.023	0.129	0.024	0.004***
ΔTier 1 Capital Ratio	-0.000	0.005	-0.000	0.007	-0.000
Deposits	1.228	0.591	1.113	0.178	-0.115***
StD(Return)	0.016	0.004	0.018	0.008	0.002***
Log(Market Cap)	7.734	1.335	5.192	0.779	-2.541***

This table presents the pre-period (before 2020Q1) comparison of the major variables. Variables are defined in Appendix A. ***, **, and * indicate the significance of the difference in means (t-tests) between treated and control banks at the 1%, 5%, and 10% levels, respectively.

Table 5. CECL's Effect on Lending-Q Sensitivity

Variable	(1)	(2) $\Delta Loan_{t+1}$	(3)
Tobin's Q	0.634***	0.512***	0.764***
	(5.49)	(3.10)	(3.95)
Treat × Tobin's Q		0.170	-0.075
		(1.49)	(-0.48)
Post × Tobin's Q			0.406***
			(3.34)
Treat × Post × Tobin's Q			**-0.245****
			(-2.05)
Treat × Post			-0.569***
			(-4.65)
Tier 1 Capital Ratio	0.332***	0.337***	0.369***
	(4.13)	(4.20)	(4.58)
Recession × Tier 1 Capital Ratio	-0.019	-0.023	-0.021
	(-0.39)	(-0.46)	(-0.46)
Δ*Tier 1 Capital Ratio*	-0.035*	-0.035*	-0.037*
	(-1.72)	(-1.72)	(-1.85)
Deposits	0.191**	0.196**	0.086
	(2.10)	(2.17)	(0.96)
StD(Return)	-0.128**	-0.106*	-0.093*
	(-2.42)	(-1.92)	(-1.73)
Log(Market Cap)	-1.401***	-1.246***	-1.925***
	(-5.17)	(-4.04)	(-5.05)
PPP	0.120***	0.125***	0.144***
	(5.90)	(5.71)	(5.85)
Observations	2,909	2,909	2,909
Adjusted R-squared	0.137	0.139	0.155
Firm Fixed Effects	Yes	Yes	Yes
Year-Quarter Fixed Effects	Yes	Yes	Yes

This table regresses lending growth ($\Delta Loan_{t+1}$) on Tobin's Q (*Tobin's Q*) interreacted with an indicator that the bank adopted CECL in 2020Q1 (*Treat*) and an indicator that the year-quarter is 2020Q1 (*Post*), controls, and fixed effects. Continuous variables are standardized. All variables are defined in Appendix A. Standard errors are clustered at the firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6. Different Loan Types

Panel A. Long-Term Homogenous Loans

Variable	(1)	(2)	(3)
	Δ*Long-Term Homogenous Loans*$_{t+1}$		
Tobin's Q	0.500***	0.640***	0.814***
	(3.90)	(3.64)	(4.19)
Treat × Tobin's Q		-0.208*	-0.320**
		(-1.80)	(-1.98)
Post × Tobin's Q			0.478***
			(3.33)
Treat × Post × Tobin's Q			**-0.361****
			(-2.51)
Observations	2,503	2,503	2,503
Adjusted R-squared	0.106	0.124	0.140
Controls	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes
Year-Quarter Fixed Effects	Yes	Yes	Yes

Panel B. Short-Term Homogenous Loans

Variable	(1)	(2)	(3)
	Δ*Short-Term Homogenous Loans*$_{t+1}$		
Tobin's Q	0.160	0.177	0.304**
	(1.60)	(1.38)	(2.05)
Treat × Tobin's Q		-0.025	-0.243*
		(-0.37)	(-1.92)
Post × Tobin's Q			0.043
			(0.44)
Treat × Post × Tobin's Q			**0.102**
			(0.87)
Observations	2,503	2,503	2,503
Adjusted R-squared	0.356	0.355	0.358
Controls	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes
Year-Quarter Fixed Effects	Yes	Yes	Yes

Panel C. Heterogenous Loans

Variable	(1)	(2)	(3)
	Δ*Heterogenous Loans*$_{t+1}$		
Tobin's Q	0.186**	0.072	0.231**
	(2.17)	(0.74)	(2.02)
Treat × *Tobin's Q*		0.169*	-0.023
		(1.93)	(-0.19)
Post × *Tobin's Q*			0.467***
			(4.37)
Treat* × *Post* × *Tobin's Q			**-0.191**
			(-1.64)
Observations	2,503	2,503	2,503
Adjusted R-squared	0.140	0.142	0.158
Controls	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes
Year-Quarter Fixed Effects	Yes	Yes	Yes

Panel A [Panel B, Panel C] regresses long-term homogenous lending growth (Δ*Long-Term Homogenous Loan*$_{t+1}$) [short-term homogenous lending growth (Δ*Short-Term Homogenous Loan*$_{t+1}$), heterogenous lending growth (Δ*Heterogenous Loan*$_{t+1}$)] on Tobin's Q (*Tobin's Q*) interreacted with an indicator that the bank adopted CECL in 2020Q1 (*Treat*) and an indicator that the year-quarter is 2020Q1 (*Post*), controls, and fixed effects separately. Continuous variables are standardized, and all variables are defined in Appendix A. Standard errors are clustered at the firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7. CECL's Effect on Lending Efficiency and Riskiness

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ROA_{t+1}		$Profit\ Margin_{t+1}$		$Asset\ Turnover_{t+1}$		$Interest\ Rate_{t+1}$	
	Lending-Q Sensitivity							
	Decrease	*Increase*	*Decrease*	*Increase*	*Decrease*	*Increase*	*Decrease*	*Increase*
Treat* × *Post	**-0.337*****	**-0.056**	**0.023**	**0.163**	**-0.196****	**0.022**	**0.058**	**-0.169**
	(-2.85)	**(-0.33)**	**(0.23)**	**(1.21)**	**(-2.56)**	**(0.24)**	**(0.58)**	**(-1.32)**
Observations	1,356	1,262	1,356	1,262	1,356	1,262	1,356	1,262
Adjusted R-squared	0.550	0.467	0.541	0.607	0.899	0.880	0.857	0.845
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Decrease − *Increase* p-value	0.000		0.007		0.000		0.000	

This table regresses *ROA*, *Profit Margin*, *Asset Turnover*, and *Interest Rate* on an indicator that the bank adopted CECL in 2020Q1 (*Treat*) interacted with an indicator that the year-quarter is 2020Q1 (*Post*), controls, and fixed effects separately for firms that experience a decrease (*Decrease*) and an increase (*Increase*) in lending-Q sensitivity after 2020Q1. The last row (*Decrease* − *Increase* p-value) presents the p-value of a 1,000-repetition bootstrap analysis testing whether the coefficients in the *Decrease* and *Increase* columns are statistically different. Continuous variables are standardized. All variables are defined in Appendix A. Standard errors are clustered at the firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8. Alternative Control and Treatment Groups

Panel A. IFRS 9 Banks as Alternative Control Group

Variable	(1)	(2) $\Delta Loan_{t+1}$	(3)
Tobin's Q	0.574***	0.829***	0.992***
	(4.66)	(3.24)	(3.82)
Treat × Tobin's Q		-0.266	-0.453*
		(-1.20)	(-1.94)
Post × Tobin's Q			0.403***
			(3.63)
Treat × Post × Tobin's Q			**-0.243****
			(-2.12)
Observations	2,431	2,431	2,431
Adjusted R-squared	0.084	0.084	0.090
Controls	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes
Year-Quarter Fixed Effects	Yes	Yes	Yes

Panel B. Small CECL Banks in 2023 as Alternative Treatment Group

Variable	(1)	(2) $\Delta Loan_{t+1}$	(3)
Tobin's Q	0.294***	0.374***	0.416***
	(3.78)	(3.13)	(2.91)
Treat × Tobin's Q		-0.092	-0.074
		(-0.90)	(-0.59)
Post × Tobin's Q			0.212**
			(2.42)
Treat × Post × Tobin's Q			**-0.196***
			(-1.85)
Observations	1,698	1,698	1,698
Adjusted R-squared	0.227	0.227	0.231
Controls	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes
Year-Quarter Fixed Effects	Yes	Yes	Yes

Panel A replicates the main tests in Table 5 using an entropy-balanced sample of IFRS 9 banks as an alternative control group. Panel B replicates the main tests in Table 5 using CECL adoption for small banks in 2023 as an alternative treatment group. Continuous variables are standardized. All variables are defined in Appendix A. Standard errors are clustered at the firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 9. Robustness Tests: Alternative Measures and Falsification

Variable	(1) $\Delta Loan_{t+1}$	(2) $\Delta Loan_{t+1}$	(3) $\Delta Loan_{t+1,loan}$
Tobin's Q adj.	0.813*** (4.19)		
Treat* × *Post* × *Tobin's Q adj.	**-0.244*** (-2.01)**		
log(Market Cap/Asset)		1.019*** (6.10)	
Treat* × *Post* × *log(Market Cap/Assets)		**-0.386*** (-3.40)**	
Tobin's Q			0.703*** (3.50)
Treat* × *Post* × *Tobin's Q			**-0.208* (-1.70)**
Observations	2,909	2,909	2,909
Adjusted R-squared	0.140	0.157	0.134
Controls	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes
Year-Quarter Fixed Effects	Yes	Yes	Yes

This table tests the robustness of our results to using alternative measures for Tobin's Q (*Tobin's Q adj.*, *log(Market Cap/Asset)*) and lending growth ($\Delta Loan_{t+1,loan}$). Continuous variables are standardized. All variables are defined in Appendix A. Standard errors are clustered at the firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.