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PROCESSING FORWARD-LOOKING LOAN LOSS PROVISIONS: EVIDENCE FROM THE ADOPTION OF THE CECL MODEL (*)

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Abstract

This paper examines the impact of the Current Expected Credit Loss (CECL) model on the efficiency with which equity investors process banks' earnings announcements. A potential concern with CECL is that it increases the complexity of loan loss provisions. I examine whether this added complexity impairs investors' ability to efficiently process earnings announcements. Using a difference-in-differences methodology, I find that CECL reduces investors' processing efficiency during banks' earnings announcements. The effect is stronger when provisions are driven by the origination of new loans. This finding is consistent with the idea that CECL introduces a timing mismatch between loss and revenue recognition—provisions for expected losses are recognized at loan origination while interest income accrues over the life of the loan—making it harder for investors to interpret the valuation implications of provisions. Collectively, my results show that equity investors face higher processing costs when interpreting banks' earnings announcements under CECL.

Keywords: CECL model, earnings announcement, investor processing efficiency.

JEL classi ication: G14, M41, G20.

Resumen

En este documento se analiza el impacto del modelo de pérdida crediticia esperada *(Current Expected Credit Loss,* CECL) sobre la eficiencia con la que los inversores en renta variable procesan los anuncios de resultados de los bancos. Una de las principales preocupaciones asociadas a este modelo es el aumento de la complejidad de las provisiones por pérdidas crediticias, lo que podría dificultar su interpretación. Mediante una metodología de diferencias en diferencias, los resultados muestran que la adopción del modelo CECL reduce la eficiencia con la que los inversores procesan los anuncios de resultados bancarios. Este efecto es más pronunciado cuando las provisiones están impulsadas por la concesión de nuevos préstamos, en línea con la idea de que el modelo CECL introduce un desajuste temporal entre el reconocimiento de pérdidas y el de ingresos. En particular, las pérdidas esperadas se reconocen en el momento de la concesión del préstamo, mientras que los ingresos por intereses se devengan a lo largo de su vida, lo que dificulta la interpretación de las implicaciones de valoración de las provisiones sobre los resultados de los bancos. En conjunto, los resultados sugieren que los inversores afrontan mayores costes de procesamiento al interpretar los anuncios de resultados bancarios bajo el modelo CECL.

Palabras clave: modelo CECL, anuncio de resultados, eficiencia de procesamiento de los inversores.

Códigos JEL: G14, M41, G20.

1. INTRODUCTION

The implementation of the Current Expected Credit Loss (CECL) model for U.S. banks has sparked significant debate over its effectiveness in improving the decision-usefulness of loan loss provisions, a key objective of the Financial Accounting Standards Board (FASB) (Gee et al., 2022; Bonsall et al., 2022; Schroeder, 2023). Under the previous methodology, the Incurred Credit Loss (ICL) model, banks recognized loan loss provisions under verifiable evidence of impairment (Beatty and Liao, 2014). Following the 2008 financial crisis, when substantial losses in banks' loan portfolios were revealed, the ICL model was criticized for leading to "too little, too late" loan loss provisions (Bischof et al., 2021; Haan and van Oordt, 2018). In response, the FASB introduced the CECL model under ASU 2016-13 in 2020, requiring US banks to recognize lifetime expected credit losses at loan origination. This shift aims to improve the timeliness of loan loss provisions and enhance transparency regarding banks' credit risk exposure (FASB, 2016).

However, critics argue that the CECL model has increased the complexity of loan loss provisions and obscured its information content, limiting its decision-usefulness (Bonsall et al., 2022; Bable et al., 2026). The estimation of lifetime expected credit losses at loan origination requires more assumptions, modeling choices and allows for greater discretion compared to the incurred loss model (López-Espinosa et al., 2021). Furthermore, the CECL model requires recognizing an expected economic loss at loan origination, even though this loss is already reflected in the loan's price, whereas interest revenue is recognized gradually over time. This mismatch between loss and revenue recognition has been criticized as counterintuitive (FASB, 2016).[1] Ultimately, the concern is that CECL makes it more difficult for investors to interpret the impact of loan loss provisions on banks' financial performance and valuation.

[1] In the preface to the Basis for Conclusions of ASU 2016-13, the two FASB board members who dissented from its issuance expressed concerns about the expected credit loss model, stating: "Originating a loan is typically a

Reflecting this debate, academic research remains inconclusive on whether CECL improves the decision-usefulness of loan loss provisions. While some studies show that CECL adoption improves information production by banks (Kim et al., 2026), and enhances the value relevance of loan loss allowances and their ability to predict future credit losses (Gee et al., 2022), others find that analysts and journalists perceive CECL provisions as less decision-useful (Bable et al., 2026), that analysts face greater challenges in forecasting loan loss provisions under the new methodology (Bonsall et al., 2022; Bonaldi et al., 2023), and that banks' earnings announcements are less informative after CECL adoption (Bonsall et al., 2022).

This paper contributes to this discussion by examining the effect of the CECL model on the processing efficiency of equity investors during banks' earnings announcements, when loan loss provisions are disclosed. Loan loss provisions, representing the largest accrual in financial institutions, are a key source of information during banks' earnings announcements (Ahmed et al., 1999; Beaver and Engel, 1996; Wahlen, 1994; Wheeler, 2021). Prior research suggests that CECL increases loan loss provisions complexity (Bonsall et al., 2022; Bable et al., 2026; Schroeder, 2023). In this paper, I examine whether this added complexity translates into higher processing costs for investors during earnings announcements, impairing their ability to efficiently interpret loan loss provisions. If the CECL model increases the complexity of loan loss provisions and reduces investor understanding of their valuation implications, processing efficiency during banks' earnings announcements is expected to decline (Barth et al., 2020; Blankespoor et al., 2020). Conversely, if loan loss provisions under CECL provide an

positive event for a lending institution, and in successful organizations, it is fundamental to long-term profitability. However, under the expected credit loss model, a growing portfolio of loans (whether through purchase or origination) will have a negative effect on profitability because of the requirement to record full lifetime expected losses when the loans are originated. [Both members] find this result puzzling and counterintuitive". (FASB, 2016). Further concerns about the increased complexity of loan loss provisions were also raised in auditors' and preparers' comment letters (see Table 1 of the Appendix B).

unambiguous signal to equity investors about expected credit losses, then investors' processing efficiency during banks' earnings announcements would remain unaffected.

Following the work of Barth et al. (2020) and Balakrishnan et al. (2022), I measure equity investor processing efficiency using the speed of resolution of investor disagreement. This measure reflects how quickly investor disagreement is resolved, as indicated by how concentrated trading volume is in the immediate periods following an earnings announcement. A faster resolution and higher value of this measure suggests higher processing efficiency, while a slower resolution indicates difficulties in processing and interpreting the newly disclosed information (Barth et al., 2020).[2] To identify the effect of the CECL model, I employ a difference-in-differences methodology, comparing publicly traded U.S. banks that adopted CECL in January 2020 (CECL banks) with those exempt from adoption until January 2023 due to their small reporting company status (ICL banks).[3] I use information from CRSP, Compustat-Banks, I/B/E/S, Thomson Reuters and S&P Capital IQ Pro to construct the main variables and controls. The sample used in the baseline analysis consists of 5,596 bank-quarters from the period 2017Q1 to 2022Q4 with sufficient data to calculate the main controls and dependent variables; this includes 139 unique CECL banks and 156 ICL banks.

My main finding is that the adoption of the CECL methodology reduces the processing efficiency of equity investors during banks' earnings announcements, as evidenced by a slower speed of resolution of investor disagreement. Specifically, the shift from the ICL model to the CECL model leads to a 2-percentage point decrease in the speed of resolution of investor disagreement. This effect is material, reducing the average pre-2020 gap in processing

[2] I focus on this volume-based measure of processing efficiency in my baseline analysis as it avoids assumptions about asset pricing models and price convergence to equilibrium, which are required in price-based approaches (see Section 3.2) (Gandhi and Lustig, 2015; Venmans, 2021; Balakrishnan et al., 2022). As a robustness check, I confirm that my results hold using alternative measures of processing efficiency that are commonly used in the literature.

[3] Regulatory deferrals and COVID-19 relief measures permitted certain banks to postpone CECL adoption (see Section 2.2). However, most banks required to adopt the model in January 2020 did so as scheduled. This study excludes banks that deferred implementation following the pandemic outbreak.

efficiency between CECL and ICL banks by 50%. Namely, before CECL adoption, CECL banks exhibited a faster resolution of investor disagreement compared to ICL banks, due to a better information environment (e.g., higher analyst coverage and institutional ownership). After CECL adoption, the decline in processing efficiency for CECL banks narrowed this gap by 50%. The finding is robust to pre-treatment trend tests and alternative definitions of equity investor processing efficiency.

The COVID-19 pandemic and the change in economic conditions pose a key challenge to the identification strategy. The heightened macroeconomic and financial uncertainty may affect both the information environment and the economic performance of banks, which in turn may be correlated with the efficiency with which equity investors process information. To address this concern, I extensively control for bank fundamentals and their information environment. Additionally, I show that my results are robust to propensity score matching, trimming the sample for larger and smaller banks, and controlling for the role of the business cycle and banks' business complexity. Furthermore, the decline in processing efficiency remains significant throughout 2021 and 2022, suggesting that the effect persists beyond 2020 and is not merely a consequence of the COVID shock.

Next, I examine two factors that may explain why the CECL model affects the processing efficiency of equity investors during banks' earnings announcements. First, I study the role of loan growth in mediating this effect. The CECL model requires recognizing expected credit losses at loan origination, even though this loss is already reflected in the loan's price, while interest revenue is recognized gradually over time. This mismatch between loss and revenue recognition becomes more pronounced when banks expand their loan portfolios. When a bank expands its loan portfolio, it must recognize a larger upfront provision for expected credit losses, reducing earnings. However, the interest revenue from these loans is recognized gradually over time. As a result, reported earnings may appear artificially low in the short term, even if the lending is profitable (FASB, 2016). Previous research shows that this asymmetry—where losses are recognized immediately while gains emerge gradually, representing a form of conditional conservatism (Qiang and Wang, 2024)— may complicate the interpretation of earnings announcements (Barth et al., 2020).

My results support this hypothesis. First, I show that after the adoption of CECL, loan growth becomes a more important determinant of loan loss provisions, as evidenced by a larger and more significant coefficient and a higher proportion of the R^2 explained by this variable. Additionally, the composition of loan portfolio growth matters—heterogeneous loans (i.e., commercial and industrial loans) account for a larger share of the variation in loan loss provisions under CECL compared to homogeneous loans (Kim et al., 2026; Ryan, 2012; Chen et al., 2025). Second, I find that this stronger link between loan growth and provisions under CECL has important implications for information processing. The negative impact on processing efficiency is most significant when loan growth drives loan loss provisions, especially for heterogeneous loans. Taken together, these results suggest that the CECL model's requirement to recognize lifetime expected credit losses at loan origination plays a key role in reducing the interpretability of loan loss provisions, especially in periods of loan growth driven by heterogeneous loans.

Next, I examine the role of opportunistic discretion under the CECL model. The adoption of the CECL model involves a higher degree of managerial discretion in estimating loan loss provisions compared to the ICL model, potentially expanding the scope for earnings management (Novotny-Farkas et al., 2024; López-Espinosa et al., 2021; Wheeler, 2021). Higher opportunistic discretion may obscure the information content of loan loss provisions (Bushman and Williams, 2012). This, in turn, may impair investors ability to understand earnings announcements, reducing processing efficiency. To evaluate this hypothesis, I consider whether the effect of the CECL model on processing efficiency is accentuated for banks that may have higher incentives to engage in such earnings management behavior, as suggested by prior research. I examine whether the effect of CECL on processing efficiency is more pronounced for banks in the top and bottom quartiles of earnings before loan loss provisions, as they are more likely to smooth earnings, and for banks in the bottom quartile of the Tier-1 capital ratio, as they may manage provisions to meet capital requirements (Beatty and Liao, 2014). The results indicate no significant differences, suggesting that any increase in opportunistic discretion under CECL does not materially affect equity investors' ability to process loan loss provisions.

This paper contributes to two main streams of research. First, it relates to the literature examining the impact of the CECL model on the decision-usefulness of loan loss provisions for market participants. Existing evidence on its implications remains mixed. On the one hand, some studies suggest that CECL improves loan loss provisions informativeness. Kim et al. (2026) find that CECL-adopting banks report timelier loan loss provisions that better reflect future non-performing loans and local economic conditions. Gee et al. (2022) show that the day-one impact of CECL on the loan loss allowance is value-relevant to equity investors and predicts future credit losses. On the other hand, other studies suggest a deterioration in banks' information environments after CECL adoption. Using return variability (U-statistic), Bonsall et al. (2022) find that after the adoption of CECL, earnings announcements become less informative. Additionally, CECL banks experience higher analyst forecast errors, greater dispersion, and reduced analyst coverage, consistent with increased uncertainty in loan loss estimates. These findings align with survey evidence from Bable et al. (2023), suggesting that analysts and financial journalists perceive CECL provisions as less decision useful. Further, Bonaldi et al. (2023) highlight concerns about earnings quality, showing that CECL adoption led to greater discretionary earnings, particularly in periods of heightened economic uncertainty.

I contribute to this literature by examining a potential channel through which the CECL model may affect the usefulness of loan loss provisions: its impact on the processing efficiency of equity investors during earnings announcements. This is a relevant dimension because the effectiveness of CECL in providing more timely and transparent assessments of credit losses may depend on how well investors understand and process the information conveyed by loan loss provisions (Schroeder, 2023; Blankespoor et al., 2020). My findings show that CECL adoption reduces processing efficiency, suggesting that the greater complexity of CECL provisions lowers their understandability, making it harder for investors to interpret and react to them in a timely manner. Overall, my findings are consistent with prior research showing that CECL increases the complexity of loan loss provisions (Bable et al., 2026; Bonaldi et al., 2023; Bonsall et al., 2022; Schroeder, 2023).

While my results may appear to diverge from research suggesting that CECL provisions enhance the prediction of future credit losses (Gee et al., 2022; Kim et al., 2026), this difference can be reconciled by accounting for the role of uncertainty in the loan loss provision estimate. A predictor can be unbiased yet exhibit high estimation uncertainty. Similarly, while CECL provisions may correctly predict average credit losses across banks (i.e., the predictor is unbiased) (Gee et al., 2022; Kim et al., 2026), the high uncertainty in the estimation makes individual bank estimates noisier and harder to interpret and predict (i.e., the predictor exhibits high variance) (Bable et al., 2026; Bonaldi et al., 2023; Bonsall et al., 2022; Schroeder, 2023).

Second, this paper contributes to the literature on the determinants of processing efficiency of equity investors during earnings announcements.[4] Barth et al. (2020) show that conditional conservatism, i.e., the asymmetry in how firms' earnings reflect good and bad news, can reduce the processing efficiency of investors. I extend this analysis to the banking sector by examining

[4] See Blankespoor et al. (2020) for a comprehensive survey of the determinants and consequences of information processing costs.

the impact of the CECL model. Under CECL, expected credit losses must be recognized upfront, while interest revenues are recorded gradually over time (Qiang and Wang, 2024). This timelier recognition of losses versus gains (i.e., conditional conservatism) may be more accentuated when loan loss provisions are driven by loan growth. In line with this idea, my findings suggest that the stronger association between loan growth and loan loss provisions may be an important channel mediating the effect of the CECL model on earnings complexity and processing efficiency.

The remainder of the paper is organized as follows. Section 2 provides the institutional background and literature review. Section 3 describes the sample and key variables. Section 4 outlines the research design and presents baseline results. Section 5 examines heterogenous effects. Section 6 conducts robustness analyses, and Section 7 concludes.

2. BACKGROUND AND RELATED RESEARCH

2.1 The ICL and CECL model

Under the Incurred Credit Loss (ICL) model, banks recognized loan loss provisions when credit losses were incurred, their occurrence was probable, and their amount was reasonably estimable (Beatty and Liao, 2014). Loan loss accounting differed by loan type, with heterogeneous loans (e.g., commercial and industrial loans) assessed individually under ASC 310-10-35 and homogeneous loans (e.g., consumer and real estate loans) evaluated collectively under ASC 450-20, allowing for earlier loss recognition based on historical loss rates. For these unimpaired homogeneous loans, banks applied a 12-month loss emergence period, while for impaired homogenous loans, provisions covered expected losses over the loan's entire remaining life (Chen et al., 2025). In contrast, commercial loans were assessed individually, and provisions were recorded only when a loan was classified as impaired, typically when default was imminent. As a result, provisions for commercial loans were often recognized later in the credit cycle compared to consumer and real estate loans, where pooling facilitated earlier recognition (Ryan, 2011; Chen et al., 2025).

The Current Expected Credit Loss (CECL) model, introduced by ASU 2016-13 and codified under ASC 326, replaces ICL by requiring banks to recognize lifetime expected credit losses at loan origination or purchase (FASB, 2016). ASU 2016-13 allows financial institutions to use different methodologies to develop the estimate of expected credit losses. For example, entities may use aging-schedule, discounted-cash flows, loss-rate, probability-of-default, or roll-rate methods.[5] Furthermore, the new accounting standard broadens both the range of data that must be considered in the estimation of credit losses and the way the data are used to estimate, for example, the probability of default (PD) and loss given default (LGD) of a loan (i.e., modeling choices) (FASB, 2016; López-Espinosa et al., 2021). This task may require historical information about the determinants of loan defaults and supportable and reasonable forecasts of GDP growth, interest rates, unemployment rates, housing prices or other macroeconomic variables under different potential scenarios.

The transition from ICL to CECL is expected to have different implications depending on loan type (Kim et al., 2026). For consumer and real estate loans, CECL replaces the 12-month loss emergence period with a lifetime expected loss approach, potentially leading to larger upfront provisions, especially for long-duration assets such as mortgages. For commercial loans, the impact of CECL can be even more pronounced. Under ICL, provisions were recorded only when a loan was classified as impaired, typically when default was imminent. CECL fundamentally shifts this approach by requiring banks to estimate lifetime expected credit losses at loan origination.

2.2 CECL Implementation Timeline and Delays

[5] See paragraph 326-20-30-3 of ASU 2016-13 (FASB, 2016).

The implementation of CECL was initially set by ASU 2016-13, which required adoption for SEC filers in fiscal years beginning after December 15, 2019, while private entities were scheduled to adopt in December 2022 (FASB, 2016). Recognizing the significant implementation costs, particularly for smaller institutions, the FASB issued ASU-2019-10 in November 2019, postponing the effective date for small reporting companies (SRCs) and emerging growth companies (EGCs) to align with the timeline for private entities (FASB, 2019).

The outbreak of COVID-19 led to further delays, as policymakers aimed to ease regulatory requirements during the crisis. On March 27, 2020, the CARES Act provided banks with the option to defer CECL adoption until December 31, 2020, or the end of the national emergency (United States Congress, 2020). This relief was later extended by the Consolidated Appropriations Act (CAA), signed into law on December 27, 2020, which postponed the deadline to January 1, 2022. Despite these deferrals, most large public financial institutions adopted CECL on January 1, 2020, disclosing its impact in their 2019 10-K filings.

2.3 Related Research

My research relates to the literature examining the impact of accounting standards on the information content of loan loss provisions and their implications for bank transparency (Acharya and Ryan, 2016; Beatty and Liao, 2014). It also relates to studies on the determinants of equity investors' processing efficiency during earnings announcements (Blankespoor et al., 2020).

Ample research has examined the implications of the ICL model on the value relevance of loan loss provisions. Studies find that higher provisions predict lower future cash flows and are associated with lower abnormal stock returns, underscoring their role as indicators of credit risk (Wahlen, 1994; Beaver and Engel, 1996; Ahmed et al., 1999; Wheeler, 2021). However, the discretionary component of loan loss provisions can significantly affect the information content of the accrual (Beatty and Liao, 2014; Bushman and Williams, 2012; Narayanamoorthy and Wheeler, 2024; Hegde and Kozlowski, 2021). For example, Bushman and Williams (2012) and Narayanamoorthy and Wheeler (2024) highlight that discretionary loan loss provisioning can either enhance market discipline by signaling forward-looking risk or weaken it by obscuring credit quality for earnings smoothing.[6]

Beyond managerial discretion, other studies have examined the extent to which loan loss provisions under ICL conveyed information about expected credit losses. Consistent with the ICL model constraining the incorporation of forward-looking information, Beatty and Liao (2021) show that including analyst provision forecasts into a model of loan loss provisions improves its ability to predict credit risk. Together with this, Wheeler (2021) finds that under ICL, banks' stock prices already reflect unrecognized expected losses, particularly in the case of larger banks with stronger information environments. This suggests that investors may infer credit risk from sources beyond financial statements.

Overall, the literature on the ICL model suggests that CECL's impact on the decision-usefulness of loan loss provisions may be driven by three key factors. First, the shift from the ICL to the CECL model may increase the predictive ability of loan loss provisions of future credit risk, potentially improving the decision-usefulness of the accrual (Beatty and Liao, 2021). Second, investors may already infer expected credit loss information from other sources, such as stress testing disclosures, reducing the incremental value of CECL provisions (Wheeler, 2021).[7] Third, the new methodology may increase the complexity of loan loss provisions, raising concerns about greater managerial discretion and reduced transparency

[6] Relatedly, Hegde and Kozlowski (2021) find that the valuation implications of discretionary provisions depend on economic conditions. Higher discretionary loan loss provisions serve as indicators of future credit losses during downturns, leading to negative abnormal returns. Conversely, in periods of economic expansion, they signal stronger future performance, resulting in positive returns.

[7] However, CECL could still enhance decision-usefulness if it forces banks to disclose proprietary risk assessments that were previously unavailable to the market. Unlike stress testing results, which follow regulatory frameworks and predefined assumptions, CECL provisions require continuous incorporation of bank-specific credit risk factors, managerial judgments, and forward-looking estimates that could reveal new insights about loan portfolio quality.

(Bushman and Williams, 2012). This paper closely relates to this third aspect by examining whether higher loan loss provision complexity may impair investors' ability to understand their valuation implications.

A more recent line of research examines the impact of IFRS 9's expected credit loss model, which replaced the incurred loss model in 2018 in most jurisdictions following International Financial Reporting Standards. López-Espinosa et al. (2021) show that IFRS 9 enhances the timeliness of loan loss recognition, suggesting a more forward-looking approach to credit risk assessment. Oberson (2021) further reports that provisions under IFRS 9 are more relevant for credit default swap pricing than under the ICL model. However, while IFRS 9 enhances the risk sensitivity of loan loss provisions, it is also shown to increase managerial discretion (Behn and Couaillier, 2026; Bischof et al., 2022; Novotny-Farkas et al., 2024; Oberson, 2021). For example, Novotny-Farkas et al. (2024) document that EU banks engage in discretionary provisioning practices, such as income smoothing, deferring the recognition of losses, and applying subjective post-model adjustments.

A strand of research more closely related to this paper examines the impact of the CECL model on the decision-usefulness of loan loss provisions. Kim et al. (2026) finds that CECL adopters' loan loss provisions better predict future non-performing loans and local economic conditions, suggesting that the model enhances the timeliness of credit risk recognition. Gee et al. (2022) show that the CECL day-one impact is value relevant to equity investors, indicating that investors incorporate this initial adjustment into their pricing decisions. However, Bonsall et al. (2022) provide evidence that, following CECL adoption, earnings announcements become less informative. In line with the findings of Bonaldi et al. (2023), they also find that CECL banks face higher analyst forecast errors, greater dispersion, and lower analyst coverage, reflecting increased uncertainty in loan loss estimates. Consistent with this explanation, Bable et al. (2026) report survey evidence indicating that market participants perceive CECL provisions as more complex and less decision-useful.

The results of this study align with prior research showing that CECL increases the complexity of loan loss provisions, making them harder for market participants to interpret and predict. The study extends prior research in three ways. First, it examines how CECL affects equity investors' processing efficiency during earnings announcements. This focus complements Bonsall et al. (2022), which assesses CECL's impact on the broader information environment of banks.[8] Second, by examining the role of provisioning at loan origination and earnings management incentives, it contributes to a broader understanding of which aspects of CECL affect users' ability to interpret loan loss provisions. Third, while Gee et al. (2022) focus on the day-one impact of CECL adoption—allowing for a direct comparison between ICL and CECL loan loss allowances under the same fundamentals—this study examines ongoing quarterly provisions reported under CECL. This distinction is important, as quarterly provisions reflect evolving macroeconomic expectations, changes in loan portfolio composition, and other dynamic factors not captured in the day-one transition.

A final area of related research examines how investors interpret and respond to new information at earnings announcements. Starting with the work of Beaver (1968), the literature has shown that earnings announcements are key events where equity investors update their valuation expectations and adjust their trading decisions (Holthausen and Verrecchia, 1990; Landsman and Maydew, 2002; Landsman et al., 2012). However, the efficiency of this process depends on the complexity and transparency of financial reporting, which can affect investors'

[8] Bonsall et al. (2022) also consider the effect of CECL on price discovery. Focusing on the intra-period price discovery (IPT) measure within a five-day window, the authors find no significant impact. My approach differs by focusing on equity investors processing efficiency as proxied by a different metric and over a longer period (Smith, 2025). In particular, the baseline analysis considers a volume-based approach capturing investor disagreement over 10, 15 or 20-day windows (Barth et al., 2020). This proxy shows low correlation with IPT, suggesting they capture distinct aspects of market behavior —with IPT reflecting the speed of information incorporation into prices, while my volume-based measure captures the persistence of investor disagreement following the disclosure of accounting information (see Section 6.2 for further discussion of how my results relate to this study).

ability to interpret earnings information (Blankespoor et al., 2020; Bloomfield, 2002; Hirshleifer and Teoh, 2003; Simon, 1978). In line with this, Barth et al. (2020) find that conditional conservatism can delay the resolution of investor disagreement during earnings announcements. I extend this analysis to the banking sector and examine how the CECL model's asymmetric recognition of losses and gains, particularly when driven by loan growth, affects processing efficiency during earnings announcements.

3. DATA AND MEASUREMENT

3.1 Data

The sample consists of U.S. banks listed in Compustat-Banks from 2017Q1 to 2022Q4 that can be linked to security-level data from CRSP. Using SEC filings and the Regulatory Database of the Federal Reserve Bank of Chicago, I classify these banks into three groups: (1) CECL banks, which adopted the CECL model in January 2020 and have used it since then; (2) Deferred banks, which postponed CECL adoption under the CARES Act after the COVID-19 outbreak (United States Congress 2020); and (3) ICL banks, which were exempt from CECL adoption until January 2023 due to their small reporting company status. To mitigate concerns that deferred banks were differentially affected by the COVID shock, I exclude them from the analysis.[9] Thus, the final sample consists of CECL banks (treatment group) and ICL banks (control group).

I construct the main dependent variables using CRSP data and obtain control variables from Compustat-Banks, I/B/E/S, Thomson Reuters, and S&P Capital IQ Pro (formerly SNL Financial), with all variables measured at a quarterly frequency. Earnings announcement data for a given quarter are matched to the corresponding bank information from the same period. Banks must have non-missing data on total assets, loan loss provisions, changes in non-

[9] Following Kim et al. (2026), I manually verify and exclude 56 banks that deferred the CECL model under the CARES act or implemented CECL after January 2020 due to a fiscal year-end other than December.

performing loans, loans-to-assets ratio, earnings before loan loss provisions, Tier 1 regulatory capital ratio, and loan portfolio composition to be included in the sample. The final sample comprises 5,596 bank-quarter observations from 295 unique banks, including 139 CECL banks and 156 ICL banks.

3.2 Measuring Investor Processing Efficiency

I follow Barth et al. (2020) and Balakrishnan et al. (2022) to measure equity investor processing efficiency, using the speed of resolution of investor disagreement around earnings announcements as a proxy for this construct. As Barth et al. (2020) explain, trading volume captures investor disagreement about the value of a security when new information arrives. In the absence of disagreement, new earnings information would be incorporated into prices immediately, without a persistent impact on trading volume. However, investors have limited resources and face constraints in processing new information (Simon, 1978; Merton, 1987; Bloomfield, 2002; Hirshleifer and Teoh, 2003). Thus, trading volume remains elevated as investors rebalance their portfolios.

Building on this intuition, Barth et al. (2020) propose capturing the speed of resolution of disagreement as the proportion of total trading volume that occurs immediately after the earnings announcement, relative to the entire announcement period. The speed of resolution of investor disagreement is defined as:

$$EA\_VOLM_{i,t} = \sum_{d=-1}^{2} VOLM_{i,t,d} \,/ \sum_{d=-1}^{20} VOLM_{i,t,d} \,, \tag{1}$$

where $VOLM_{i,t,d}$ represents the ratio of daily trading volume to total outstanding shares for every firm i in day d around the earnings announcement date ($d = 0$) corresponding to calendar quarter t. The numerator of *EA_VOLM* corresponds to the sum of $VOLM_{i,t,d}$ during the announcement window *(*$d = -1,0,1,2$*)*. The denominator is constructed as the sum of $VOLM_{i,t,d}$ during the complete announcement period *(*$d = -1,0,\ldots,20$*)*. Thus, $EA\_VOLM_{i,t}$

represents the proportion of investor disagreement in the announcement window relative to the complete announcement period. A higher value of *EA_VOLM* implies a faster resolution of investor disagreement, as more trading volume is concentrated in the immediate earnings announcement window. Conversely, a lower value indicates that a larger share of trading volume is spread across the full announcement period, suggesting a slower resolution of disagreement and, consequently, lower equity investor processing efficiency in incorporating new information. To evaluate the robustness of my results, I also construct this measure using shorter announcement periods of 10 and 15 days.

This volume-based measure offers several advantages over alternative measures used in the literature. First, because *EA_VOLM* is a ratio of trading volume in the initial announcement window to that of the full announcement period, the magnitude of pre-announcement volume does not influence its construction (Barth et al., 2020). If trading volume were instead scaled by pre-announcement levels, those values would cancel out in both the numerator and denominator, making the measure robust to pre-event activity. Second, unlike price-based measures, this approach avoids the need to specify an asset pricing model, which is particularly relevant given the lack of consensus on the appropriate factor model for financial institutions (Ghandi and Lustig, 2015; Venmans, 2021). Third, price-based measures assume that stock prices converge to an equilibrium within a predetermined window, requiring researchers to impose assumptions about the timing of mean reversion (Balakrishnan et al., 2022). Overall, by focusing on trading activity rather than price movements, this volume-based measure provides a direct and model-independent way to assess investor processing efficiency during banks' earnings announcements.

3.3 Alternative Measures of Investor Processing Efficiency

To assess the robustness of my results, I also consider alternative proxies for investor processing efficiency that are commonly used in the literature. First, I use the measure developed by Balakrishnan et al. (2022), which is a volume-based analogue to the metric used to assess the speed of intra-period price discovery (Butler et al., 2007; Bushman et al., 2010). Intuitively, IPT_VOLM captures how quickly trading volume incorporates all available information following an earnings announcement. It is defined as:

$$IPT_{VOLM_{i,t}} = \sum_{d=-1}^{20} \left(\frac{CUM\_VOLM_{\mathrm{i,t,d}}}{CUM\_\mathrm{VOLM}_{i,t}} \right) + \frac{1}{2}, \tag{2}$$

where CUM_VOL is the cumulative volume over the period -2 to +20 around the earnings announcement of firm i referring to the financial results of quarter t. $CUM\_VOL_{i,t,d}$ is the cumulative volume from day -2 to day d in the earnings announcement window. The ratio $CUM\_VOLM_{i,t,d}/CUM\_VOLM$ is computed for each day d and finally added over the -2 to 20 window to yield *IPT_VOLM*.[10]

Second, I consider two price-based measures of investor processing efficiency. On the one hand, I use the volatility of equity returns to capture the uncertainty about the consensus belief or market equilibrium price of a security (Barth et al., 2020). While changes in investors' expectations could cause higher trading volume, a change in the consensus belief of the firm's value is a necessary condition to observe higher equity return volatility after the arrival of new information to market participants (Barth et al., 2020). Similar to the previous measures, I capture the speed of resolution of uncertainty as the ratio of the volatility immediately surrounding the earnings announcement relative to that of the full announcement period. Hence, I define the speed of resolution of investors uncertainty during earnings announcements as:

$$EA\_VOLA_{i,t} = \sum_{d=-1}^{2} VOLA_{i,t,d} \,/ \sum_{d=-1}^{20} VOLA_{i,t,d}\,, \tag{3}$$

[10] This formula calculates the area under a curve by summing up the areas of trapezoids formed for each daily time interval (Bushman et al., 2010).

where $VOLA_{i,t,d}$ is the square of the abnormal stock return of bank i around the earnings announcement date ($d = 0$) corresponding to calendar quarter t. I estimate the abnormal return as the difference between the realized return and the expected return based on the Fama-French three-factor model estimated in a preannouncement period of 360 trading days before $d = 0$. For robustness, I also consider this measure using the CAPM model and the asset pricing model suggested in (Gandhi and Lustig, 2015). *EA_VOLA* captures the proportion of equity return volatility that occurs immediately surrounding the announcement period. A lower (higher) value of *EA_VOLA* implies a slower (faster) speed of resolution of uncertainty around the earnings announcement.

Lastly, I consider intra-period timeliness (IPT) as an additional price-based measure of investor processing efficiency. IPT is calculated as:

$$IPT\_5d_{i,t} = \sum_{d=0}^{4} \frac{CAR_{i,t,d}}{CAR_{i,t,5}}, \tag{4}$$

where $CAR_{i,t,d}$ represents the cumulative abnormal buy-and-hold return from day 0 through day d corresponding to calendar quarter t. I estimate the abnormal return as the difference between the realized return and the expected return based on the Fama-French three-factor model estimated in a preannouncement period of 360 trading days before $d = 0$.

3.4 Descriptive Statistics

Table 1, Panel A, presents the summary statistics for the main variables used in the analysis. The descriptives of *EA_VOLM* show that, on average, 22% (median: 21%) of trading volume occurs in the initial earnings announcement period relative to the full announcement period. Regarding *VOLM_IPT*, the mean (median) is 12.93 (13.05). When considering price-based proxies of processing efficiency, the average (median) speed of resolution of investor uncertainty during earnings announcements, *EA_VOLA,* is 30% (26%). These magnitudes align with the descriptive statistics reported in Barth et al. (2020).[11]

Table 1, Panel B, presents summary statistics for the CECL (treated) and ICL (control) banks throughout the sample period, highlighting key differences between the two groups. CECL banks exhibit a significantly faster speed of resolution of investor disagreement, as indicated by the higher *EA_VOLM* values. These banks tend to be larger and have a higher market beta. CECL banks also operate in a richer information environment, as evidenced by higher analyst coverage and institutional ownership. In contrast, there are no significant differences in abnormal returns, loan growth, change in non-performing loans, return volatility or the S&P 500 return during the earnings announcement window. Additionally, CECL banks have slightly higher loan loss provisions and earnings before loan loss provisions, as well as lower Tier 1 capital ratios, though the differences are economically small. The composition of loan portfolios also differs, with CECL banks having a lower proportion of real estate loans but a higher share of commercial and industrial loans and consumer loans.

Throughout the analysis, I account for differences between ICL and CECL banks by incorporating time-varying controls, including bank fixed effects, and allowing the impact of banks' portfolio composition to vary over time. To ensure that observed differences do not drive the results, I conduct several robustness tests (see Section 6.1). These include propensity score matching to pair CECL and ICL banks with similar information environments, trimming the sample by excluding the smallest and largest banks and controlling for the role of the business cycle and banks' inherent complexity.

3.5 Assessing *EA_VOLM* as a Proxy for Investor Processing Efficiency

[11] Barth et al. (2020) focus on the speed of resolution of investor disagreement and uncertainty for the case of non-financial firms between 1994 and 2011. They document an average (median) speed of resolution of investor disagreement at earnings announcements of 25% (24%). The average (median) speed of resolution of investor uncertainty is 35% (30%).

EA_VOLM has been proposed in the literature as a proxy for equity investors' processing efficiency (see Section 3.2). Its validity relies on two main assumptions: (1) banks' earnings announcements, when loan loss provisions are disclosed, introduce new information that leads to increased trading volume, and (2) trading volume exhibits persistence (i.e. it does not immediately revert to pre-announcement levels). To support the use of *EA_VOLM* in this setting, I assess whether these assumptions hold in my sample. Figure 1 plots average daily trading volume, scaled by shares outstanding. It shows a sharp increase in volume on day 0, followed by a gradual decline in the days after. This pattern suggests that earnings announcements generate new information and that investor disagreement—and thus elevated trading activity—persists beyond the initial release.

Table 2 reports the correlations between *EA_VOLM* and other measures of equity investor processing efficiency, as well as characteristics of banks' information environments. *EA_VOLM* and *IPT_VOLM* are strongly positively correlated, suggesting they capture a common underlying construct. Both also correlate positively with *EA_VOLA*. Additionally, all three measures are positively correlated with bank size, market sensitivity, analyst coverage, and institutional ownership, indicating that banks with a stronger information environment experience a faster resolution of investor disagreement (Barth et al. 2020). In contrast, intra-period price discovery over a five-day window (*IPT_5d*) exhibits only weak correlations with both the volume-based processing efficiency measure and banks' information environment. This divergence may reflect the shorter measurement window of *IPT_5d* and its reliance on price adjustments rather than trading volume or volatility (Smith 2025; Balakrishnan et al. 2022).

Finally, in Table 3, I present descriptive regressions examining the determinants of *EA_VOLM*. Column (1) shows that greater analyst coverage (*Analyst*) and higher institutional ownership (*Inst*) are associated with higher processing efficiency, supporting the idea that a stronger information environment facilitates quicker incorporation of new information (Healy and Palepu 2001). Column (2) controls the logarithm of banks' total assets (*Size*). The effect of *Analyst* becomes weakly significant, suggesting its effect is largely driven by bank size, while *Inst* remains significant but with a reduced coefficient. Column (3) introduces quarter fixed effects and other bank level controls, and Column (4) includes bank fixed effects to control for time-invariant bank-specific heterogeneity. With these controls, both *Analyst* and *Inst* become insignificant, likely due to their stability over time. Overall, both Table 2 and Table 3 suggest that *EA_VOLM* is positively associated with other proxies of processing efficiency employed in the literature and with banks' information environments, supporting its validity as a proxy for investor processing efficiency

4. CECL ADOPTION AND INVESTOR PROCESSING EFFICIENCY

4.1 Baseline Analysis

The estimation of lifetime expected credit losses at loan origination under CECL raises the concern of higher complexity of loan loss provisions, making their valuation implications more difficult to interpret. If the CECL model increases the complexity of loan loss provisions and reduces investor understanding of their valuation implications, processing efficiency during banks' earnings announcements is expected to decline (Simon, 1978; Bloomfield, 2002; Hirshleifer and Teoh, 2003; Blankespoor et al., 2020). Thus, I hypothesize that the added complexity of CECL relative to the ICL model may reduce investor processing efficiency at banks' earnings announcements.

To investigate whether the adoption of the CECL model is associated with a lower processing efficiency of equity investors during earnings announcements, I estimate the following difference-in-differences (DiD) regression:

$$EA\_VOLM_{it} = \beta\, CECL_i \times Post_t + \gamma' X_{it} + \alpha_i + \delta_t + u_{it}\,. \quad (5)$$

The dependent variable EA_VOLM_{it} captures equity investor processing efficiency during banks' earnings announcements, measured by the speed of resolution of investor disagreement. This variable is based on the earnings announcements of bank i for the financial results of calendar quarter *t* (see Section 3.2). *CECL* is an indicator variable that takes a value equal to one for banks that adopted the CECL model in January 2020 (CECL banks) and zero for banks under the ICL model until January 2023 (ICL banks). *Post* is an indicator variable equal to one for the period after the year 2020. The coefficient β captures the DiD effect which compares the average speed of resolution between CECL banks and ICL banks after the introduction of the CECL model, relative to the difference between the two groups under the ICL methodology. *X* includes bank-level time-varying control.[12] All control variables are measured at a quarterly frequency and correspond to bank i's information at the end of calendar quarter t. Finally, α and δ indicate bank and time (quarter-year) fixed effects, respectively. Standard errors are clustered at the bank level.

Table 4 presents the baseline results. Column (1) reports an unconditional DiD regression, estimated without controls or fixed effects. The coefficient on *CECL* × *Post* is negative and significant, indicating that CECL adoption reduces *EA_VOLM*, which reflects a decline in equity investor processing efficiency during earnings announcements. The positive and significant coefficient on *CECL* suggests that, before CECL adoption, these banks exhibited higher *EA_VOLM*, consistent with a stronger information environment and more efficient investor processing. In Column (2), I introduce bank-level controls, bank fixed effects, and time fixed effects. The coefficient on *CECL* × *Post* is negative and statistically significant,

[12] Specifically, I control for analyst coverage, institutional ownership, banks' abnormal returns and S&P 500 return around the earnings announcement, the bank's return volatility during the quarter, market beta, bank size, the change in non-performing loans, Tier 1 capital ratio, earnings before loan loss provisions, loan growth, and loan portfolio composition (i.e., *Consumer/TA, C&I/TA, RealEstate/TA*), as well as the interaction of each portfolio share with the *Post* indicator. All continuous variables are winsorized at the 1 and 99 level. See Appendix A for variable definitions.

reinforcing the baseline finding that CECL adoption reduces equity investor processing efficiency during earnings announcements.

Column (3) restricts the sample to one year before and after CECL adoption to better isolate its immediate impact while minimizing the influence of long-term trends. The results remain robust, suggesting that the decline in equity investor processing efficiency is attributable to CECL adoption rather than broader long-term dynamics. Column (4) excludes the year 2020 and finds similar results, addressing concerns that the COVID shock may have disproportionately affected larger banks in the treatment group, potentially confounding the main result. Section 6 further explores this endogeneity concern and tests the robustness of the baseline finding.

In terms of magnitude, the results show that CECL adoption reduces *EA_VOLM* by approximately 2 percentage points. This effect is substantial, closing 50% of the average pre-2020 gap in processing efficiency between CECL and ICL banks. Before CECL adoption, CECL banks resolved investor disagreement more quickly than ICL banks, likely due to a stronger information environment (e.g., higher analyst coverage and institutional ownership). However, after CECL adoption, the decline in processing efficiency among CECL banks reduced this advantage by half.

4.2 Parallel Trends and Dynamic Effects

The parallel trends assumption requires that, absent CECL adoption, the difference in investor processing efficiency between CECL and ICL banks would have remained unchanged. While this assumption cannot be directly tested, it can be assessed by examining whether pre-treatment trends in equity investor processing efficiency differ between the two groups. To this end, I replace the *Post* variable in the baseline regression with a series of semester-level time indicators (i.e., covering two calendar quarters per period). Figure 2 plots the estimated coefficients for these indicators with 95% confidence intervals, allowing for an evaluation of both pre-trends and the dynamics of the CECL effect over time. The results show no evidence of preexisting trends, as the estimated coefficients for the pre-CECL period are statistically indistinguishable from zero.

The figure also highlights key dynamics in the impact of CECL adoption. First, the decline in equity investor processing efficiency extends beyond 2020, indicating that the findings are not driven by the outbreak of the COVID-19 pandemic. Instead, the effect persists across multiple post-adoption periods. Second, the estimated impact weakens by late 2022, suggesting that the decline in processing efficiency may be temporary. This pattern may be consistent with investors adapting to CECL and improving their ability to interpret loan loss provisions over time. It may also reflect enhanced disclosure practices by banks, which may help mitigate initial challenges in processing CECL-related information (Bonsall et al., 2022).

4.3 Alternative Definitions of Investor Processing Efficiency

Table 5 reports the estimates of Equation (5) using alternative definitions of equity investor processing efficiency. In all specifications, I include bank-level controls, as well as bank and time fixed effects. In Columns (1) and (2), I modify the *EA_VOLM* measure by adjusting the length of the complete earnings announcement window to 15 and 10 days, respectively. The results remain consistent with the baseline. Column (3) uses *IPT_VOLM* as an alternative volume-based measure of processing efficiency (Balakrishnan et al., 2022). I find a negative and significant effect of CECL adoption, further supporting the conclusion that CECL slows the resolution of investor disagreement.

In Columns (4) to (6), I use different asset pricing models to measure *EA_VOLA*, capturing the speed of resolution of investor uncertainty during earnings announcements. In particular, Column (4) relies on the estimation of abnormal return using the Fama-French three-factor model, Column (5) extends this model by including bond risk factors following Ghandi and Lustig (2015), and Column (6) employs the market model. Across all specifications, the negative and significant effect of CECL adoption on processing efficiency persists, indicating that the baseline result is robust to this alternative definition of investor processing efficiency. Finally, Column (7) examines IPT_5d, a price-based measure of information incorporation speed over a window of five days, and finds no significant effect. This suggests that CECL adoption does not impact intra-period price discovery within the first five days after earnings announcements, in line with the findings of Bonsall et al. (2022).[13]

5. HETEROGENOUS EFFECTS

5.1 The Role of Provisioning at Loan Origination

5.1.1 Loan Growth and Loan Loss Provisions

Under CECL, expected credit losses are recognized at loan origination, while interest revenue accrues over time. This mismatch intensifies when banks expand their loan portfolios, as higher provisions immediately reduce earnings, even when lending remains profitable (FASB 2016). This asymmetry—where losses are recognized upfront, but gains emerge gradually—reflects conditional conservatism, which may complicate investors' interpretation of loan loss provisions and earnings announcements (Barth et al., 2020; Qiang and Wang, 2024).

The hypothesis that provisions driven by the origination of new loans may accentuate the negative effect of CECL on processing efficiency is based on the premise that loan growth is a key determinant of loan loss provisions under CECL. To test this, I estimate a regression examining how the effect of loan growth (i.e. the growth rate of total loans and leases, $\Delta Loan$) varies over time and between CECL and ICL banks. Given CECL's requirement to provision at loan origination, this association is expected to be stronger post-adoption for banks that follow the new impairment model. I regress loan loss provisions on potential determinants,

[13] See Section 6.2 for further discussion on how my results complement the findings in Bonsall et al. (2022).

allowing the effect of loan growth to differ across time and bank groups. Specifically, I estimate the following regression separately for CECL banks and ICL banks:

$$LLP_{it} = \beta_1\, \Delta Loan_{it} + \beta_2\, \Delta Loan_{it} \times Post_t \;+ \gamma' X_{it} + \alpha_i + \delta_t + u_{it,} \qquad (6)$$

where LLP denotes loan loss provisions, $\Delta Loan_{it}$ is the growth rate of loans, $Post_t$ is the indicator variable defined in Equation (6) and X_{it} denotes a set of loan loss provisions determinants.[14] α_i and δ_t denote bank and quarter-year fixed effects, respectively.

Table 6 presents the results. Under the ICL model (Columns (1) and (2)), loan growth ($\Delta Loan$) is positively associated with loan loss provisions, suggesting that expanding credit may involve lending to riskier borrowers (Beatty and Liao, 2014). For ICL banks, the interaction term $\Delta Loan \times Post$ is not significant, indicating that this relationship remains unchanged after 2020. In contrast, for CECL banks (Columns (3) and (4)), the interaction term $\Delta Loan \times Post$ is positive and statistically significant, showing that after 2020, loan growth plays a larger role in determining loan loss provisions. This result is consistent with CECL's requirement to recognize expected credit losses at origination.[15]

To further analyze the role of loan growth in explaining the variation of loan loss provisions, I estimate the following model separately for CECL and ICL banks, as well as for the periods before and after 2020,

$$LLP_{it} = \beta_1\, \Delta Loan_{it} + \gamma' X_{it} + \alpha_i + \delta_t + u_{it}, \qquad (7)$$

and perform a Shapley value decomposition of R^2. The Shapley value quantifies the relative contribution of each explanatory variable to the overall model fit by decomposing R^2 into the proportion attributable to each determinant. Specifically, I group variables into five categories

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[14] I control for the current change in non-performing loans, bank size, earnings before loan loss provisions to total assets, the Tier 1 regulatory capital ratio and the composition of the loan portfolio (Bushman and Williams 2012). In columns 2 and 4, I interact these variables with the indicator variable *Post*.

[15] The difference in the *Post*×*ΔLoans* coefficient between ICL and CECL banks is significantly different from zero at conventional levels. Untabulated results confirm this pattern when estimating Equation (6) by pooling all observations and examining the differential effect between CECL and ICL banks, relative to their pre-treatment difference (i.e., the triple interaction *CECL*×*Post*×*ΔLoans*).

(loan growth, size, non-performing loan dynamics, capital and earnings measures and loan portfolio composition) to compare their explanatory power[16].

Figure 3 presents the results separately for ICL and CECL banks before and after CECL adoption. Panel A (before 2020) shows that loan growth accounted for a small proportion of the total variation in loan loss provisions, explaining 1.1% of R^2 for CECL banks and 4.5% for ICL banks. This suggests that, under the ICL model, loan growth played a modest role in determining provisions. After CECL adoption (Panel B), the contribution of loan growth to the variation in loan loss provisions increased significantly for CECL banks. Loan growth now explains 17.8% of R^2 for CECL banks, compared to 5.3% for ICL banks, highlighting its greater relevance under the new model.

Finally, I examine whether the impact of loan growth on provisioning varies by loan type. To do this, I modify Equation (7) by replacing aggregate loan growth with the growth rates of specific loan categories: consumer loans, real estate loans, and commercial and industrial loans. Figure 3, Panels C and D, present the Shapley value decomposition for these specifications. The results indicate that under CECL, commercial and industrial (C&I) loan growth plays the largest role in explaining the variation in loan loss provisions. This finding aligns with the notion that CECL's requirement to provision for lifetime expected losses at loan origination has a greater impact on heterogeneous loan types, such as C&I loans, which exhibit more borrower-specific risk and less standardized credit characteristics compared to consumer or real estate loans (Chen et al., 2025; Kim et al., 2026; Ryan, 2012).

5.1.2 Loan Growth and Investor Processing Efficiency

I proceed by examining the effect of loan growth-driven loan loss provisions on investor processing efficiency. To quantify this effect, I first estimate the sensitivity of loan loss

[16] Loan portfolio composition include the share of consumer loans, commercial and industrial loans and real estate loans to total assets.

provisions to loan portfolio expansion. Specifically, I regress loan loss provisions on loan growth, allowing the effect to differ between CECL and ICL banks and across the post-2020 period. The regression model is specified as follows: [17]

$$LLP_{it} = \alpha + \rho_1\, CECL_i \times\ Post_t \times \Delta Loan_{it} + \rho_2' Interactions_{it} + u_{it}. \quad (8)$$

Using the estimated coefficients from Equation (8), I construct the variable *Fitted_LLP*, which captures the expected variation in loan loss provisions driven by loan portfolio expansion:

$$Fitted\ LLP\ _{it} = \hat{\rho}_1\, CECL_i \times\ Post_t \times \Delta Loan_{it} + \widehat{\rho_2'} Interactions_{it.} \quad (9)$$

Thus, *Fitted_LLP* isolates the portion of loan loss provisions attributable to loan growth, controlling for other observed and unobserved determinants. By construction, it is orthogonal to other loan loss provision determinants, ensuring that it accurately captures the loan growth-driven component of provisions.

Table 7 presents the results. In Columns (1)–(3) I define *HighLLP* as an indicator variable taking value equal to one for banks in the top 50th, 75th, or 80th percentiles of *Fitted_LLP* in every calendar quarter, respectively. Columns (4)–(6) replicate these specifications but exclude the year 2020 to ensure that the results are not driven by the COVID-19 shock. Consistent with the baseline results, the coefficient on *CECL* × *Post* remains negative and significant, indicating that the CECL model reduces investor processing efficiency. More importantly, the coefficient on *CECL* × *Post* × *HighLLP* is also negative and statistically significant, suggesting that the effect of CECL is amplified when banks experience greater loan portfolio expansion. The result remains robust to excluding 2020. Overall, these findings align with the hypothesis that a key source of CECL's complexity is the ambiguous impact of loan loss provisions on bank valuation due to provisioning at loan origination (FASB, 2016).

[17] Specifically, I estimate an OLS model without controls and without bank or quarter fixed effects. I include all double interactions between the variables *CECL, Post* and Δ*Loan.*

Next, I examine whether the relationship between loan growth and investor processing efficiency differs by loan type. I classify loans into heterogeneous loans (commercial and industrial loans) and homogeneous loans (consumer and real estate loans). I replicate Equation (8), identifying loan loss provisions that are primarily driven by the expansion of each loan type. The focus is on banks where fitted LLP is above the 80th percentile. Table 8 presents the results. Columns (1) and (2) focus on heterogeneous loans, with Column (2) excluding 2020. Columns (3) and (4) analyze homogeneous loans, with Column (4) similarly excluding 2020.

Consistent with the baseline results, *CECL* × *Post* remains negative and significant across all specifications. Notably, the interaction term *CECL* × *Post* × *HighLLP* is significantly negative only for heterogeneous loans. This suggests that the negative effect of CECL on processing efficiency is more pronounced when loan loss provisions are driven by commercial and industrial loan expansion. This result aligns with the discussion in Section 2.3, which highlights that the shift from ICL to CECL has a greater impact on loan loss provisions for heterogeneous loans (Kim et al., 2022; Ryan, 2012; Chen et al., 2025).

5.2 The Role of Opportunistic Discretion

5.2.1 Pre-provisions Earnings, Regulatory Capital and Loan Loss Provisions

The CECL model gives bank managers greater discretion in determining loan loss provisions (López-Espinosa et al., 2021). Prior research highlights two opportunistic uses of this discretion. First, managers can use loan loss provisions to smooth earnings to make the bank's financial performance appear more stable and predictable (Healy and Wahlen, 1999; Dechow et al., 2010; Beatty and Liao, 2014). Second, discretion in loan loss provisioning can be used to avoid breaching regulatory capital limits (Kim and Kross, 1998; Ahmed et al., 1999). I expect the effect CECL model on equity investor processing efficiency to be more pronounced when opportunistic discretion plays a more significant role in determining loan loss provisions, obscuring its information content (Bushman and Williams, 2012)

As a first step, I investigate whether the CECL model has increased earnings management by US banks by examining the relationship between loan loss provisions, earnings, and regulatory capital before and after CECL adoption (Bushman and Williams, 2012; López-Espinosa et al., 2021). Earnings smoothing is expected to imply a positive association between earnings before loan loss provisions and the provisions themselves. Regulatory capital management suggests a positive association between loan loss provisions and regulatory capital. If the CECL model has increased managerial discretion and managers use it opportunistically, these existing associations would be strengthened. To investigate this, I run regressions that control for potential determinants of loan loss provisions and allow the effects of earnings and regulatory capital to vary over time. Specifically, I estimate the following regression for ICL and CECL banks:

$$LLP_{it} = \beta_1\, EBLLP_{it} + \beta_2\, EBLLP_{it} \times Post_t + \beta_3\, \mathrm{Tier1Cap_{it}} + \beta_4\, \mathrm{Tier1Cap_{it}} \times Post_t + \gamma' X_{it} + \alpha_i + \delta_t + u_{it} \tag{10}$$

Table 9 presents the results for ICL banks (Columns (1)– (2)) and CECL banks (Columns (3)– (4)). The coefficient on *EBLLP* is positive and significant across all specifications, indicating that loan loss provisions are positively associated with pre-provision earnings, consistent with earnings smoothing behavior (Bushman and Williams, 2012). However, the interaction term *EBLLP* × *Post* is not significantly positive for CECL banks, suggesting that the adoption of CECL has not increased the use of provisions for earnings management. Regarding regulatory capital, the coefficient on *Tier1Cap* is positive and significant for CECL banks, implying that higher capital levels are associated with higher provisions. However, the negative and significant coefficient on *Tier1Cap* × *Post* suggests that after CECL adoption, the sensitivity of provisions to capital levels declines. This finding is inconsistent with the notion that CECL increased regulatory capital management. Overall, these results suggest that the new accounting model has not significantly changed the relation between loan loss provisions and either earnings or regulatory capital.

5.2.2 Opportunistic Discretion and Investor Processing Efficiency

Next, I examine whether the negative effect of the CECL model on equity investor processing efficiency varies depending on banks' incentives for earnings management. On the one hand, I analyze banks in the upper and lower quartiles of the earnings before loan loss provisions distribution. The earnings smoothing hypothesis predicts that institutions with higher earnings may have incentives to increase provisions, while those with lower earnings may seek to decrease them (Beatty and Liao, 2014). On the other hand, I focus on banks in the lower quartile of the Tier 1 regulatory capital ratio distribution, as these banks may have stronger incentives to underreport loan loss provisions to maintain adequate regulatory capital levels.

Table 10 presents the results. Column (1) focuses on banks in the upper quartile of earnings before loan loss provisions (*EBLLP*). The interaction term *CECL* × *Post* × *High EBLLP* is negative and significant at the 5% level, suggesting that investor processing efficiency declines more for these banks under CECL. However, when excluding the year 2020 (Column (4)), the coefficient loses significance, indicating that the effect may have been influenced by the COVID-19 period. Columns (2) and (5) examine banks in the lower quartile of *EBLLP,* while Columns (3) and (6) focus on banks in the lower quartile of the Tier 1 capital ratio. In both cases, the interaction terms are not significant in the full sample or when excluding 2020, suggesting that lower-earnings banks and undercapitalized banks do not experience a differential impact of CECL on processing efficiency.[18]

[18] An alternative approach is to first estimate discretionary loan loss provisions and then examine whether the effect of CECL on investor processing efficiency is more pronounced when discretionary provisions are higher (Beatty and Liao, 2014). Untabulated results, following the methodology of López-Espinosa et al. (2021) to estimate discretionary provisions, find no significant differential effects. Consistent with the evidence of Table 10, this suggests that discretionary provisioning does not drive the observed impact on processing efficiency.

Overall, these findings provide limited evidence that opportunistic discretion in loan loss provisioning under CECL exacerbates the effect on investor processing efficiency. This suggests two possible interpretations. First, banks may not use the increased discretion provided by the CECL model for opportunistic motives. For instance, regulatory and auditor oversight may effectively constrain earnings and capital management, aligning with the evidence in Table 9. Second, even if banks engage in opportunistic discretion, it may not materially affect investors' ability to process the valuation implications of loan loss provisions during earnings announcements (Table 10).

6. ROBUSTNESS TESTS AND ADDITIONAL ANALYSES

6.1 The Role of the COVID Shock and Banks' Information Environment

The onset of the COVID-19 pandemic in March 2020 and the resulting economic disruption poses a significant challenge to my identification strategy. The simultaneous implementation of CECL and the abrupt macroeconomic changes during the treatment period create the concern of confounding effects.[19] Moreover, the macroeconomic shock may have had heterogeneous effects on CECL-adopting banks, potentially influencing their information environment, performance, and operations. Figure 4 presents a causal graph illustrating these interdependencies.

In Table 11, I propose five robustness tests to ensure that the observed effects of CECL adoption on equity investor processing efficiency stem from the new accounting standard itself rather than external factors. Column (1) restricts the sample to banks with positive analyst coverage and introduces additional controls for analyst dispersion, the proportion of analysts

[19] The direction of the bias is unclear. CECL banks are on average larger than ICL banks. The onset of the COVID pandemic, a global shock, may have affected more investors' information processing efficiency for CECL banks, which are potentially more exposed to global risks. On the other hand, CECL banks have a better information environment and may be more resilient to uncertainty shocks compared to smaller, more opaque banks. This could lead to a reduced impact of uncertainty shocks on equity investors information processing efficiency for CECL banks

missing earnings forecasts, and institutional ownership. These variables are interacted with the indicator *Post* to allow for a differential effect of banks' information environments on processing efficiency before and after CECL adoption. The estimated coefficient on *CECL* × *Post* remains negative and statistically significant, suggesting that changes in analyst behavior or institutional investor presence do not confound the negative effect of the new impairment model on equity investors processing efficiency.

Column (2) applies a propensity score matching procedure, pairing CECL banks with ICL banks that had similar average levels of analyst coverage, dispersion, and institutional ownership before implementation (2017–2019).[20] While this reduces the sample size, the results remain consistent, indicating that differences in banks' pre-existing information environments do not account for the decline in equity investor processing efficiency. Column (3) tests whether the results are driven by differences in bank size by trimming the sample, removing banks in the bottom 25% and top 25% of the size distribution. The estimated effects remain unchanged, reducing the likelihood that extreme size differences between CECL and ICL banks drive the observed effect.

Column (4) examines the role of macroeconomic conditions by interacting *CECL* with changes in the coincident index at the state level, based on the location of each bank's headquarters (Kim et al., 2022). This allows for differences in how treated and control banks respond to economic fluctuations. The results remain robust, suggesting that business cycle effects do not confound the findings. Finally, Column (5) controls for the role of banks' business complexity by interacting the indicator *Post* with the textual complexity measure from Loughran and McDonald (2023) and the length of banks' 10-K filings. These measures capture

[20] I use nearest-neighbor matching with a caliper of 0.02, ensuring that each CECL bank is matched to the closest non-CECL bank within a maximum allowable difference of 0.02 in propensity scores. Results are robust to the choice of caliper size, as similar findings are obtained when using stricter (0.01) and more relaxed (0.025 and 0.05) calipers. None of the matched covariates differ significantly between CECL and ICL banks, indicating that the groups are statistically similar after matching.

differences in financial disclosure practices before and after 2020 and serve as proxies for banks' inherent business complexity (Blankespoor et al., 2020). The estimated coefficient on *CECL* × *Post* remains significant, confirming that reporting complexity does not drive the results. Taken together, these tests help confirming that the negative impact of CECL on equity investors processing efficiency is robust to controlling for banks' information environment, size, changes in economic conditions, and inherent complexity.

6.2 Processing Efficiency and Value Relevance during Earnings Announcements

Bonsall et al. (2022) examine the impact of the CECL model on the informativeness of earnings announcements, analyst loan loss provision forecasts, and 10-K/Q filings. Using return variability, as measured by Beaver (1968) U-statistic (*UStat*), they find that earnings announcements become less informative following CECL adoption.[21] My findings suggest a complementary channel: CECL also impairs the efficiency with which equity investors process accounting information. These two effects are not mutually exclusive—rather, they may operate simultaneously. A decline in the clarity or precision of loan loss provision disclosures (i.e., lower information content) can interact with heightened processing costs, making it more difficult for investors to interpret and incorporate the information efficiently (Blankespoor et al. 2020).

While Bonsall et al. (2022) provide robust evidence that the decline in the information content of earnings announcement is not driven by reduced processing efficiency, I further explore this possibility. To this end, I construct the *UStat* measure, confirming similar descriptive statistics to the ones presented in Bonsall et al. (2022). I then examine whether the documented decline in informativeness, as captured by the *UStat* measure, remains robust

[21] UStat captures the information content of financial disclosures by comparing return volatility during the event window [0, +1] (relative to an earnings announcement) with the variance of residual returns in the estimation period (i.e. the window [-130, -10] and [+10, +130]).

when controlling for equity investors' processing efficiency, as captured by the speed of resolution of investor disagreement during earnings announcements (Barth et al. 2020).

Table 12 presents the results of this analysis. Column (1) shows that CECL adoption is associated with a decline in *UStat*, consistent with a reduction in the value relevance of loan loss provisions during earnings announcements. Column (2) adds the *EA_VOLM* proxy to control for processing efficiency. The coefficient on the *CECL* × *Post* interaction remains negative and statistically significant, suggesting that the decline in informativeness is not mediated by changes in investor processing efficiency during earnings announcements. Columns (3) and (4) repeat the analysis excluding observations from the year 2020, to ensure the results are not driven by COVID-related disruptions. The findings remain consistent. Taken together, these results reinforce the conclusion that CECL reduces the information content of loan loss provisions even after accounting for investor processing efficiency, suggesting that both mechanisms are at play.

7. CONCLUSION

The implementation of the CECL model has sparked significant debate about its effectiveness in enhancing the decision-usefulness of loan loss provisions, a key objective of the Financial Accounting Standards Board. Proponents argue that CECL improves the timeliness and predictive value of loan loss provisions by requiring banks to recognize expected credit losses at loan origination. However, critics argue that CECL increases the complexity of loan loss provisioning. One concern is that losses must be recognized at loan origination, which can create a mismatch between the timing of loss recognition and revenue generation. CECL also increases reliance on forward-looking assumptions and managerial discretion, adding complexity to loan loss provisioning.

I predict and find that the CECL model reduces the average processing efficiency of equity investors during earnings announcements, with a stronger effect for banks with high loan growth, particularly when driven by heterogeneous loans. However, I find weak or no significant differences for banks with stronger incentives to use loan loss provisions for earnings management. This suggests that the higher earnings complexity introduced by CECL stems primarily from the ambiguous impact of loan loss provisions on bank valuation during loan portfolio expansion, rather than from concerns about increased opportunities for managerial discretion. Collectively, my results show that CECL increases the complexity of loan loss provisions and impairs investors' ability to interpret their valuation implications. This evidence is relevant for regulators and academics conducting post-implementation reviews of the new impairment model

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Figure 1- Evolution of Trading Volume Around Earnings Announcements

This figure illustrates the average daily trading volume (*VOLM*), defined as trading volume divided by shares outstanding, around earnings announcements. The sample period is from 2017Q1 to 2022Q4. I consider a window of 10 days before and 10 days after the earnings announcement date (day 0). All continuous variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Appendix A.

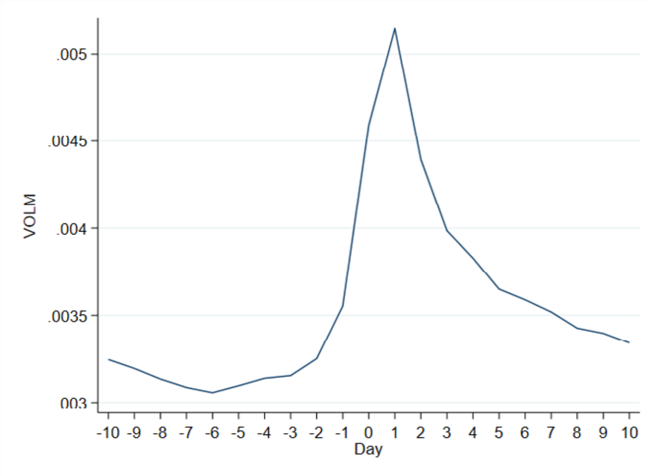


Figure 2- Pre-Treatment Trends and Dynamic Effects

This figure presents the estimated coefficients from a regression where the *Post* variable in the baseline specification (Equation (5)) is replaced with a series of semester-level time indicators, each covering two calendar quarters. The plotted coefficients represent the estimated effects over time, with 95% confidence intervals. The sample period is from 2017Q1 to 2022Q4. The regression includes *Analyst, ABRET, Inst, RetVol, SP500 ret, Beta, Size, LLP, ΔNPL, Tier1Cap, EBLLP, ΔLoan, Consumer/TA, C&I/TA, RealEstate/TA,* and the interaction between loan portfolio composition and Post as controls, along with quarter and bank fixed effects. All continuous variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Appendix A.

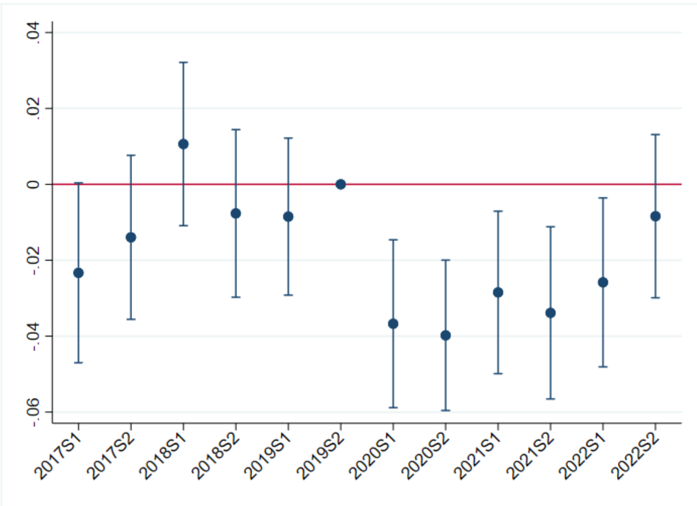
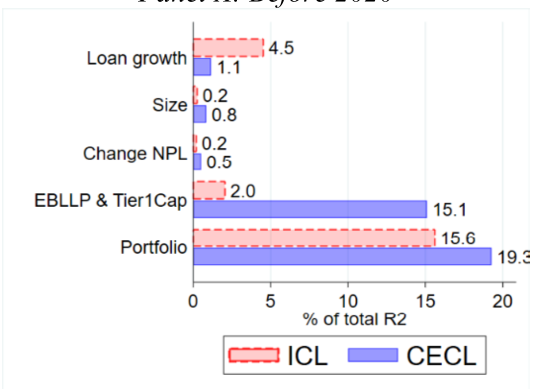


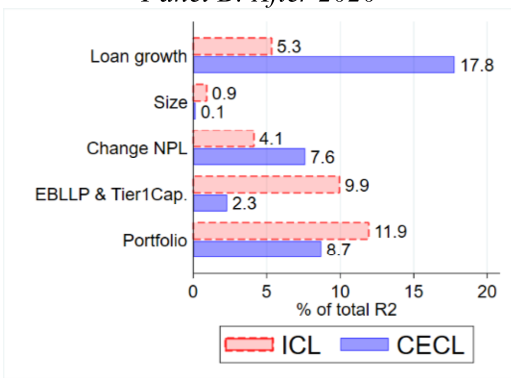
Figure 3- Shapley Value Decomposition of Loan Loss Provisions

This figure presents the Shapley value decomposition of the R^2 of a loan loss provision model (Equation 7), quantifying the relative contribution of different explanatory variable categories to the variation in loan loss provisions. Determinants are grouped into five categories: loan growth, size, non-performing loan dynamics, capital and earnings measures, and loan portfolio composition (*Consumer/TA, C&I/TA, RealEstate/TA)*. The decomposition is shown separately for ICL and CECL banks before and after CECL adoption. Panel A reports results for the period before CECL adoption (pre-2020). Panel B shows results after CECL adoption (post-2020). Panels C and D present the decomposition using loan growth disaggregated by loan type. The sample period is from 2017Q1 to 2022Q4. All continuous variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Appendix A.

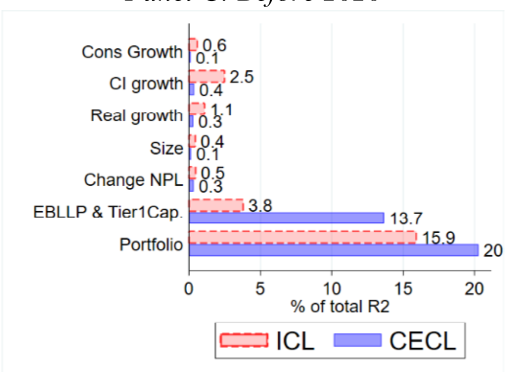
Panel A: Before 2020



Panel B: After 2020



Panel C: Before 2020



Panel D: After 2020

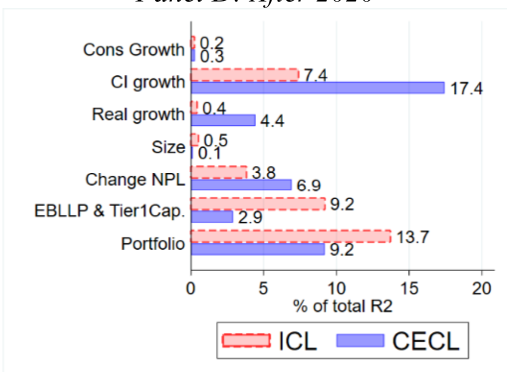


Figure 4- Conceptual Framework Linking CECL Adoption, Economic Conditions, and Investor Processing Efficiency

This figure depicts the potential channels through which CECL adoption, changes in economic conditions, and bank fundamentals influence the processing efficiency of equity investors at earnings announcements.

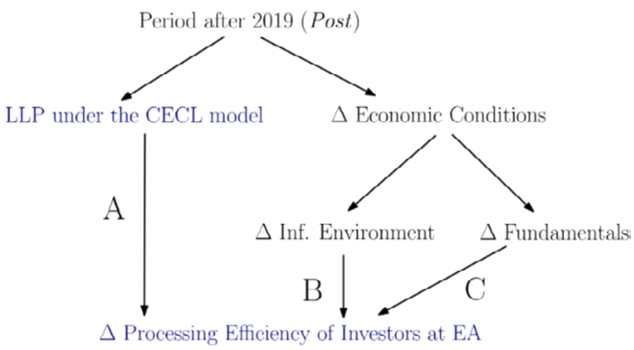


Table 1- Descriptive Statistics

Panel A presents summary statistics for the key dependent and control variables used in the regressions over the sample period from 2017Q1 to 2022Q3. Panel B presents summary statistics for the key variables separately for banks reporting under the incurred credit loss (mean-ICL) model and those reporting under the current expected credit loss (mean-CECL) model. The table reports the mean for each group, the difference in means (CECL - ICL), and the p-value from a t-test for the equality of means. All continuous variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Appendix A.

Panel A

	(1) **mean**	(2) **sd**	(3) **p25**	(4) **p50**	(5) **p75**	(6) **N**
Post	0.5175	0.4997	0.0000	1.0000	1.0000	5,596
EA_VOLM	0.2149	0.0818	0.1639	0.2131	0.2608	5,596
VOLM_IPT	12.9342	1.4121	12.2281	13.0527	13.7944	5,596
EA_VOLA	0.3030	0.2065	0.1351	0.2586	0.4419	5,596
IPT_5d	3.5961	8.8404	2.1695	3.6058	5.1754	5,596
Analyst	1.4412	0.9401	0.6931	1.6094	2.0369	5,596
ABRET	-0.1270	4.5739	-2.6433	-0.1909	2.4414	5,596
Inst	0.5518	0.2696	0.3290	0.5612	0.7693	5,596
RetVol	0.0209	0.0118	0.0139	0.0172	0.0232	5,596
SP500_ret	0.0695	0.6611	-0.2456	0.0864	0.4815	5,596
Beta	0.7343	0.4426	0.4103	0.8499	1.0616	5,596
Size	8.6433	1.6767	7.3336	8.3960	9.6736	5,596
LLP	0.0006	0.0012	0.0000	0.0003	0.0008	5,596
Tier1Cap	0.1255	0.0231	0.1099	0.1213	0.1360	5,596
Δ NPL	-0.0003	0.0020	-0.0009	-0.0002	0.0003	5,596
EBLLP	0.0039	0.0014	0.0031	0.0039	0.0046	5,596
ΔLoan	0.0272	0.0606	-0.0008	0.0146	0.0360	5,596
Consumer/TA	0.0328	0.0472	0.0031	0.0120	0.0441	5,596
C&I/TA	0.1226	0.0775	0.0651	0.1074	0.1629	5,596
RealEstate/TA	0.5175	0.1616	0.4229	0.5316	0.6282	5,596

Panel B

	Mean-ICL	Mean-CECL	Diff (CECL-ICL)	p-value
EA VOLM	0.1931	0.2314	0.0383	0
Analyst	0.6623	2.0219	1.3596	0
ABRET	-0.1230	-0.1871	-0.0641	0.6575
Inst	0.3348	0.7099	0.3751	0
RetVol	0.0216	0.0206	-0.0009	0.1416
SP500 ret	0.0008	0.0006	-0.0002	0.3092
Beta	0.4625	0.9525	0.4900	0
Size	7.2656	9.6762	2.4106	0
LLP	0.0005	0.0006	0.0002	0.0026
Tier1Cap	0.1300	0.1238	-0.0061	0.0183
ΔNPL	-0.0003	-0.0002	0.0001	0.4605
EBLLP	0.0035	0.0042	0.0007	0
ΔLoan	0.0272	0.0274	0.0001	0.9498
Consumer/TA	0.0260	0.0366	0.0106	0.0417
C&I/TA	0.1068	0.1364	0.0297	0.0005
RealEstate/TA	0.5844	0.4672	-0.1171	0

Table 2- Correlation Matrix

This table presents the unconditional (Pearson) correlation matrix for proxies and determinants of investor processing efficiency during bank earnings announcements. The sample period is from 2017Q1 to 2022Q4. All continuous variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Appendix A.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) EA_VOLM	1							
(2) VOLM_IPT	0.7296	1						
(3) EA_VOLA	0.3089	0.2332	1					
(4) IPT_5d	0.0462	0.0263	0.0878	1				
(5) Inst	0.2319	0.2083	0.2697	0.0401	1			
(6) Beta	0.2038	0.1753	0.2512	0.0431	0.5710	1		
(7) Size	0.2579	0.2135	0.2537	0.0500	0.6920	0.6463	1	
(8) Analyst	0.2336	0.1881	0.2211	0.0497	0.5843	0.5599	0.8577	1

Table 3- Determinants of Investor Processing Efficiency at Earnings Announcements

This table presents descriptive regressions examining the determinants of *EA_VOLM*, the main proxy for investor processing efficiency during bank earnings announcements used in the analyses. The table reports conditional correlations with key control variables used in the baseline analysis. Column (1) includes variables capturing the bank's information environment, while Column (2) additionally controls for bank size. Column (3) introduces quarter fixed effects and additional bank-level controls, and Column (4) includes bank fixed effects to account for time-invariant bank-specific heterogeneity. Additional bank level controls include *LLP, ΔNPL, Tier1Cap, EBLLP, ΔLoan, Consumer/TA, C&I/TA, RealEstate/TA*, and the interaction between loan portfolio composition and the variable *Post*. All continuous variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Appendix A. Standard errors are clustered at the bank level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dep.Variable	EA_VOLM (1)	EA_VOLM (2)	EA_VOLM (3)	EA_VOLM (4)
Analyst	0.0096***	0.0035*	0.0027	-0.0013
	(0.0019)	(0.0020)	(0.0023)	(0.0034)
ABRET	-0.0012	-0.0009	0.0023*	0.0019
	(0.0012)	(0.0012)	(0.0013)	(0.0013)
Inst	0.0086***	0.0065***	0.0056***	-0.0007
	(0.0018)	(0.0019)	(0.0018)	(0.0046)
RetVol	-0.0042***	-0.0041***	0.0041**	0.0004
	(0.0010)	(0.0010)	(0.0019)	(0.0025)
SP500_ret	0.0028***	0.0028***	0.0018	0.0023*
	(0.0011)	(0.0010)	(0.0012)	(0.0012)
Beta	0.0063***	0.0043**	0.0034**	0.0023
	(0.0017)	(0.0017)	(0.0016)	(0.0030)
Size		0.0109***	0.0115***	0.0166
		(0.0024)	(0.0026)	(0.0175)
Observations	5,596	5,596	5,596	5,596
Ad. R-squared	0.0714	0.0764	0.1066	0.1448
Other bank controls	No	No	Yes	Yes
Bank FE	No	No	No	Yes
Quarter FE	No	No	Yes	Yes

Table 4- The CECL Model and Equity Investor Processing Efficiency

This table presents the results for the DiD regression (Equation (5)) examining the impact of CECL adoption on *EA_VOLM*, the main proxy for investor processing efficiency during bank earnings announcements. The sample period is from 2017Q1 to 2022Q4. Column (1) reports an unconditional specification without controls or fixed effects. Column (2) includes bank-level controls, bank fixed effects, and time fixed effects. Column (3) restricts the sample to one year before and after CECL adoption. Column (4) excludes the year 2020. Additional bank-level controls include *Analyst, ABRET, Inst, RetVol, SP500 ret, Beta, Size, LLP, ΔNPL, Tier1Cap, EBLLP, ΔLoan, Consumer/TA, C&I/TA, RealEstate/TA*, and the interaction between loan portfolio composition and *Post.* All continuous variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Appendix A. Standard errors are clustered at the bank level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dep.Variable	EA_VOLM *Whole sample* (1)	EA_VOLM *Whole sample* (2)	EA_VOLM *2019-2020* (3)	EA_VOLM *Without COVID* (4)
Post	0.0035			
	(0.0040)			
CECL	0.0501***			
	(0.0041)			
CECL × Post	-0.0210***	-0.0230***	-0.0341***	-0.0189***
	(0.0047)	(0.0058)	(0.0092)	(0.0066)
Observations	5,596	5,596	1,885	4,621
Ad. R-squared	0.0636	0.1480	0.1502	0.1510
Controls	No	Yes	Yes	Yes
Bank FE	No	Yes	Yes	Yes
Quarter FE	No	Yes	Yes	Yes

Table 5- Alternative Definitions of Investor Processing Efficiency

This table presents DiD regressions (Equation (5)) using alternative definitions of equity investor processing efficiency. The sample period is from 2017Q1 to 2022Q4. Columns (1) and (2) modify EA_VOLM by adjusting the length of the earnings announcement window to 15 and 10 days, respectively. Column (3) replaces EA_VOLM with VOLM_IPT, an alternative volume-based measure of processing efficiency. Columns (4) to (6) estimate EA_VOLA using different asset pricing models: the Fama-French three-factor model (Column 4), the extended Fama-French model with bond risk factors (Column 5), and the market model (Column 6). Column (7) examines IPT_5d, a price-based measure of information incorporation speed. All regressions include bank-level controls, bank fixed effects, and quarter fixed effects. Additional bank-level controls include *Analyst, ABRET, Inst, RetVol, SP500 ret, Beta, Size, LLP, ΔNPL, Tier1Cap, EBLLP, ΔLoan, Consumer/TA, C&I/TA, RealEstate/TA,* and the interaction between loan portfolio composition and Post. All continuous variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Appendix A. Standard errors are clustered at the bank level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dep.Variable	EA_VOLM	EA_VOLM	VOLM_IPT	EA_VOLA	EA_VOLA	EA_VOLA	IPT_5d
	15 days	*10 days*	*(Balakrishnan et al., 2022)*	*(Barth et al., 2020)*	*(Gandhi and Lustig, 2015)*	*Market model*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CECL × Post	-0.0201***	-0.0232***	-0.3786***	-0.0598***	-0.0526***	-0.0797***	0.3713
	(0.0067)	(0.0082)	(0.0963)	(0.0123)	(0.0126)	(0.0117)	(0.5674)
Observations	5,596	5,596	5,596	5,596	5,596	5,596	5,596
Adj. R-squared	0.1357	0.1118	0.1144	0.1824	0.1968	0.1883	0.0014
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 6- Loan Loss Provisions and Loan Growth

This table presents the association between loan growth and loan loss provisions, controlling for other potential determinants (Equation 7). I consider the sample period from 2017q1 to 2022q4. The dependent variable is loan loss provisions to total (lagged) loans (LLP). Columns 1 and 2 show the results for the sample of banks that use the ICL model until January 2023 (ICL banks). Columns 3 and 4 show the results for the sample of banks using the CECL model since January 2020 (CECL banks). In all specifications, I control for *Size, ΔNPL, Tier1Cap, EBLLP Consumer/TA, C&I/TA and RealEstate/TA*. In Columns 2 and 4 I include the interaction between these variables and Post. Variable definitions are provided in Appendix A. Continuous variables are winsorized at the 1% and 99% level. Standard errors are clustered at the bank level and reported in brackets. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Dep.Variable	LLP *ICL banks* (1)	LLP *ICL banks* (2)	LLP *CECL banks* (3)	LLP *CECL banks* (4)
Δ Loans	0.0020***	0.0020***	-0.0008	0.0007*
	(0.0007)	(0.0007)	(0.0007)	(0.0004)
Δ Loans × Post	-0.0006	-0.0006	0.0070***	0.0065***
	(0.0009)	(0.0009)	(0.0009)	(0.0010)
Observations	2,467	2,467	3,129	3,129
Adj. R-squared	0.4004	0.4050	0.6165	0.6197
Controls	Yes	Yes	Yes	Yes
Controls × Post	No	Yes	No	Yes
Bank FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes

Table 7- Loan Loss Provisions Driven by Loan Growth and Investor Processing Efficiency

This table presents DiD regressions (Equation (5)) examining the relationship between loan loss provisioning at origination and investor processing efficiency during bank earnings announcements. The sample period is from 2017Q1 to 2022Q4. The dependent variable is *EA_VOLM*, the main proxy for investor processing efficiency. *HighLLP* is an indicator variable equal to one for banks in the top 50th, 75th, or 80th percentiles of *Fitted_LLP* within each calendar quarter. Columns (1)–(3) estimate the model for the full sample, while Columns (4)–(6) exclude the year 2020. All regressions include bank-level controls, bank fixed effects, and quarter fixed effects. Additional bank-level controls include *Analyst, ABRET, Inst, RetVol, SP500 ret, Beta, Size, LLP, ΔNPL, Tier1Cap, EBLLP, ΔLoan, Consumer/TA, C&I/TA, RealEstate/TA*, and the interaction between loan portfolio composition and *Post*. All continuous variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Appendix A. Standard errors are clustered at the bank level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Whole Sample			*Without COVID*		
Dep.Variable *HighLLP=*	EA_VOLM Above pc 50 (1)	EA_VOLM Above pc 75 (2)	EA_VOLM Above pc 80 (3)	EA_VOLM Above pc 50 (4)	EA_VOLM Above pc 75 (5)	EA_VOLM Above pc 80 (6)
CECL × Post	-0.0122*	-0.0179***	-0.0193***	-0.0077	-0.0151**	-0.0159**
	(0.0071)	(0.0061)	(0.0061)	(0.0097)	(0.0071)	(0.0069)
CECL × Post × HighLLP	-0.0544***	-0.0574***	-0.0490***	-0.0564***	-0.0506***	-0.0510***
	(0.0162)	(0.0175)	(0.0176)	(0.0173)	(0.0171)	(0.0180)
Observations	5,596	5,596	5,596	4,621	4,621	4,621
Adjusted R-squared	0.1497	0.1497	0.1494	0.1526	0.1523	0.1522
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 8- Loan Loss Provisions Driven by Heterogenous or Homogenous Loan Growth and Investor Processing Efficiency

This table presents DiD regressions (Equation (5)) examining the relationship between loan loss provisioning at origination and investor processing efficiency during bank earnings announcements, distinguishing between heterogeneous (commercial and industrial) loans and homogeneous (consumer and real estate) loans. The sample period is from 2017Q1 to 2022Q4. The dependent variable is EA_VOLM, the main proxy for investor processing efficiency. *HighLLP* is an indicator variable equal to one for banks in the top 80th percentile of *Fitted_LLP* within each calendar quarter. Columns (1) and (2) focus on heterogeneous loan growth, while Columns (3) and (4) analyze homogeneous loan growth. Columns (2) and (4) exclude the year 2020. All regressions include bank-level controls, bank fixed effects, and quarter fixed effects. Additional bank-level controls include *Analyst, ABRET, Inst, RetVol, SP500 ret, Beta, Size, LLP, ΔNPL, Tier1Cap, EBLLP, ΔLoan, Consumer/TA, C&I/TA, RealEstate/TA,* and the interaction between loan portfolio composition and Post. All continuous variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Appendix A. Standard errors are clustered at the bank level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Whole sample	*Without COVID*	*Whole sample*	*Without COVID*
Dep.Variable	EA_VOLM	EA_VOLM	EA_VOLM	EA_VOLM
HighLLP=	CI growth-80	CI growth-80	Homog. growth-80	Homog. growth-80
	(1)	(2)	(3)	(4)
CECL × Post	-0.0205***	-0.0154**	-0.0207***	-0.0183**
	(0.0062)	(0.0071)	(0.0061)	(0.0072)
CECL × Post x HighLLP	-0.0665***	-0.0653***	-0.0471*	-0.0413
	(0.0180)	(0.0184)	(0.0265)	(0.0257)
Observations	5,596	4,621	5,596	4,621
Ad. R-squared	0.1494	0.1523	0.1484	0.1512
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes

Table 9- Loan Loss Provisions and Earnings Management Incentives

This table examines the relationship between loan loss provisions (*LLP*), earnings before loan loss provisions (*EBLLP*), and regulatory capital (*Tier1Cap*) before and after CECL adoption. The sample period is from 2017Q1 to 2022Q4. The dependent variable is *LLP*, and the analysis is conducted separately for ICL banks (Columns 1–2) and CECL banks (Columns 3–4). The interaction terms *EBLLP* × *Post* and *Tier1Cap* × *Post* allow for changes in these relationships after CECL adoption.. In all specifications, the regression includes bank-level controls, bank fixed effects, and quarter fixed effects. Bank-level controls include *Size, ΔNPL, Tier1Cap, EBLLP, Consumer/TA, C&I/TA*, and *RealEstate/TA*. Columns (2) and (4) additionally including interactions of controls with *Post*. All continuous variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Appendix A. Standard errors are clustered at the bank level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	ICL Banks		*CECL Banks*	
Dep.Variable	LLP	LLP	LLP	LLP
	(1)	(2)	(3)	(4)
EBLLP	0.0756*	0.0647*	0.0970*	0.0858*
	(0.0456)	(0.0385)	(0.0521)	(0.0455)
EBLLP × *Post*	0.0561	0.0726*	-0.0407	-0.0195
	(0.0490)	(0.0429)	(0.0545)	(0.0456)
Tier1Cap	-0.0014	-0.0017	0.0092**	0.0069*
	(0.0021)	(0.0019)	(0.0045)	(0.0035)
Tier1Cap × *Post*	-0.0022	-0.0024	-0.0070**	-0.0044
	(0.0021)	(0.0023)	(0.0027)	(0.0027)
Observations	2,467	2,467	3,129	3,129
Ad. R-squared	0.4015	0.4047	0.5952	0.6224
Controls	Yes	Yes	Yes	Yes
Controls x Post	No	Yes	No	Yes
Bank FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes

Table 10- Earnings Management Incentives and Investor Processing Efficiency

This table presents the results for the DiD regression (Equation (5)) examining whether the impact of CECL adoption on investor processing efficiency (EA_VOLM) varies based on banks' incentives for earnings management. The sample period is from 2017Q1 to 2022Q4. Columns (1) and (4) focus on banks in the upper quartile of earnings before loan loss provisions (High EBLLP), while Columns (2) and (5) analyze banks in the lower quartile of EBLLP (Low EBLLP). Columns (3) and (6) examine banks in the lower quartile of the Tier 1 capital ratio (Low T1Cap). Columns (4)–(6) exclude the year 2020. All regressions include bank-level controls, bank fixed effects, and quarter fixed effects. Additional bank-level controls include *Analyst, ABRET, Inst, RetVol, SP500 ret, Beta, Size, LLP, ΔNPL, Tier1Cap, EBLLP, ΔLoan, Consumer/TA, C&I/TA, RealEstate/TA*, and the interaction between loan portfolio composition and *Post*. All continuous variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Appendix A. Standard errors are clustered at the bank level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Whole Sample			*Without COVID*		
Dep.Variable	EA_VOLM	EA_VOLM	EA_VOLM	EA_VOLM	EA_VOLM	EA_VOLM
	(1)	(2)	(3)	(4)	(5)	(6)
CECL × Post	-0.0174***	-0.0213***	-0.0247***	-0.0147**	-0.0184***	-0.0245***
	(0.0066)	(0.0062)	(0.0066)	(0.0074)	(0.0070)	(0.0077)
CECL × Post × High EBLLP	-0.0254**			-0.0175		
	(0.0123)			(0.0139)		
CECL × Post × Low EBLLP		-0.0053			-0.0017	
		(0.0116)			(0.0131)	
CECL × Post × Low T1Cap			0.0132			0.0255*
			(0.0116)			(0.0131)
Observations	5,596	5,596	5,540	4,621	4,621	4,586
Ad. R-squared	0.1482	0.1478	0.1493	0.1513	0.1508	0.1521
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 11- Robustness Tests

This table presents DiD regressions (Equation (5)) testing the robustness of the relationship between CECL adoption and investor processing efficiency (*EA_VOLM*) to alternative specifications and potential confounding factors. The sample period is from 2017Q1 to 2022Q4. Column (1) restricts the sample to banks with positive analyst coverage and introduces additional controls for banks' information environments. Column (2) applies propensity score matching, pairing CECL banks with non-CECL banks based on pre-implementation characteristics. Column (3) trims the sample by removing banks in the bottom and top 25% of the size distribution. Column (4) accounts for macroeconomic conditions by interacting CECL with changes in the coincident index at the state level. Column (5) introduces controls for bank complexity, using a textual complexity measure and the size of banks' 10-K filings. All regressions include bank-level controls, bank fixed effects, and quarter fixed effects. Additional bank-level controls include *Analyst, ABRET, Inst, RetVol, SP500 ret, Beta, Size, LLP, ΔNPL, Tier1Cap, EBLLP, ΔLoan, Consumer/TA, C&I/TA, RealEstate/TA*, and the interaction between loan portfolio composition and *Post*. All continuous variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Appendix A. Standard errors are clustered at the bank level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dep.Variable	EA_VOLM *Information environment* (1)	EA_VOLM *Propensity Score Matching* (2)	EA_VOLM *Trimming the sample* (3)	EA_VOLM *Coincident Index* (4)	EA_VOLM *Bank complexity* (5)
CECL × Post	-0.0234***	-0.0266**	-0.0244***	-0.0228***	-0.0295***
	(0.0070)	(0.0110)	(0.0067)	(0.0059)	(0.0070)
Observations	4,082	1,436	2,721	5,524	4,508
Ad. R-squared	0.2054	0.1362	0.1242	0.1479	0.1407
Controls	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes

Table 12- Investor Processing Efficiency and Value Relevance

This table presents regressions examining the relationship between investor processing efficiency and the informativeness of earnings announcements, as measured by the U-statistic (*UStat*) from Beaver (1968). The sample period is from 2017Q1 to 2022Q4. The table replicates the DiD analysis of Bonsall et al. (2022) by estimating the effect of CECL adoption on *UStat*. Columns (1) and (2) present results for the full sample, while Columns (3) and (4) exclude the year 2020. All regressions include bank-level controls, bank fixed effects, and quarter fixed effects. Bank-level controls include *Analyst, ABRET, Inst, RetVol, SP500 ret, Beta, Size, LLP, ΔNPL, Tier1Cap, EBLLP, ΔLoan, Consumer/TA, C&I/TA, RealEstate/TA*, and the interaction between loan portfolio composition and *Post*. All continuous variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Appendix A. Standard errors are clustered at the bank level and reported in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Whole Sample		*Without COVID*	
Dep.Variable	UStat	UStat	UStat	UStat
	(1)	(2)	(3)	(4)
CECL x Post	-3.5976**	-3.2173**	-4.9189**	-4.6215**
	(1.3985)	(1.3909)	(1.9132)	(1.9161)
EA_VOLM		1.3459***		1.2874***
		(0.2447)		(0.2752)
Observations	5,594	5,594	4,619	4,619
Adjusted R-squared	0.6733	0.6761	0.7101	0.7124
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes

Appendix A- Variable definitions

Variable	Description
ABRET	Signed cumulative excess return in the initial announcement period based on the Fama and French (1993) three-factor model. Source: CRSP and Kenneth French - Data Library.
Analyst	Logarithm of the average number of analysts following a bank in the calendar quarter. Source: I/B/E/S.
Beta	Coefficient on the excess market return over the risk-free rate from the model used to calculate expected return when constructing *EA_VOLA*. Source: CRSP, Kenneth French - Data Library.
C&I/TA	Proportion of commercial and industrial loans to total assets. Source: Capital IQ Pro.
CECL	Indicator variable taking value equal to one for banks estimating loan loss provisions under the CECL model since January 2020 and 0 otherwise. Source: 10-K,10-Q SEC Filings and Regulatory Database of the Federal Reserve Bank of Chicago.
Coindex	Quarterly change in the weighted average of the state-level coincident index based on the location of banks' headquarters. Source: Federal Reserve Bank of Philadelphia
Consumer/TA	Proportion of consumer loans to total assets. Source: Capital IQ Pro.
Dispersion	Standard deviation of analyst forecasts in the calendar quarter. Source: I/B/E/S.
EA_VOLA	Proportion of the cumulative volatility (square sum of abnormal returns) occurring during the initial announcement period [-1,2], relative to the sum of volatility occurring during the whole announcement period [-1,20]. Abnormal returns are computed based on the Fama-French (1993) three-factor model. As a robustness, I also consider the CAPM model and the factor model proposed in Ghandi and Lustig (2015). Source: CRSP, Kenneth R. French - Data Library and Global Financial Data.
EA_VOLM	Proportion of the cumulative volume to shares outstanding occurring during the initial announcement period [-1,2], relative to the cumulative volume to shares outstanding occurring during the whole announcement period [-1,20]. Source: CRSP.
EBLLP	Net income before loan loss provisions divided by lagged total assets. Source: Compustat-Banks.
HighLLP	Indicator variable equal to one for banks in the top 50th, 75th, or 80th percentile of Fitted_LLP in each calendar quarter, and zero otherwise. Fitted_LLP is the fitted value from a regression of loan loss provisions as specified in Equation (8). It captures the component of provisions attributable to loan portfolio expansion, isolating it from other determinants.
ICL	Indicator variable taking value equal to one for banks estimating loan loss provisions under the ICL model until January 2023 and 0 otherwise. Source: 10-K,10-Q SEC Filings and Regulatory Database of the Federal Reserve Bank of Chicago.
Inst	Percent of shares held by institutional investors in the calendar quarter. Source: Thomson Reuters.
IPT_5d	Proportion of the total cumulative abnormal return (CAR) realized within the first five days following an earnings announcement ([0,4] window) relative to the cumulative abnormal return over the full five-day period ([0,5] window). Abnormal returns are estimated using the Fama-French three-factor model based on a preannouncement estimation period of 360 trading days before day 0. Source: CRSP, Kenneth R. French - Data Library and Global Financial Data.
IPT_VOLM	Sum of the proportion of cumulative volume to shares outstanding from -2 to +20 days to total cumulative volume to shares outstanding around the earnings announcement, plus one half. This formula approximates the area under the graph that is depicted by the series of ratios of cumulative volume at day d to total cumulative volume. Source: CRSP.
LLP	Quarterly loan loss provisions divided by lagged total loans. Source: Compustat-Banks.
Post	Indicator variable taking value equal to one for periods after 2019q4 and 0 otherwise.
Real Estate/TA	Proportion of real estate loans to total assets. Source: Capital IQ Pro.
RetVol	The daily return volatility measured over the previous calendar quarter leading up to the earnings announcement. Source: CRSP.
Size	Logarithm of the bank's total assets lagged one period. Source: Compustat-Banks.
SP500_ret	The average return of the S&P 500 index during the initial earnings announcement window [-1,2] for a given bank. Source: FRED from the St. Louis Federal Reserve.
Tier1Cap	Tier 1 regulatory capital ratio lagged one period. Source: Compustat-Banks.
UStat	The proportion of stock return variance occurring during the earnings announcement window [0,+1], relative to the variance of residual returns over the estimation period [-130,-10] ∪ [+10,+130]. Source: CRSP, Kenneth R. French - Data Library.
VOLM	Trading volume to total shares outstanding. Source: CRSP
ΔLoans	Growth rate of loans relative to the previous calendar quarter. Source: Compustat-Banks.
ΔNPL	Change in non-performing loans divided by lagged total loans. Source: Compustat-Banks.

Appendix B- Extracts from comment letters to Financial Instruments—Credit Losses (Subtopic 825-15) (emphasis added).

Wells Fargo: Comment Letter No. 175
"While it is positive that the FASB proposal permits a significant amount of flexibility, attempts by preparers to satisfy the objective of a lifetime loss estimate will likely **yield a wide range of potential loan loss allowance estimates**. For example, some financial institutions may employ a mean reversion approach that assumes credit losses will never exceed historical loss experience while other institutions may employ a more sophisticated path dependent approach that incorporates different economic assumptions during the remaining contractual life of a financial asset or portfolio of financial assets. Given the significant judgment involved in selecting the methodologies and assumptions to measure lifetime credit losses for assets that do not exhibit signs of impairment, **we expect a significant amount of diversity in the application of the proposed guidance that will ultimately inhibit comparability among peers and impair the usefulness of financial information**."
Ernst & Young: Comment Letter No. 305
"Using management's forecast- (…) Auditing an entity's forecast would present challenges, particularly when entities base their conclusions on different forecasts. Both the proposal and the FAQ document indicate that an entity would use forecasts that reflect management's expectations. **Auditors would then have to corroborate management's expectations with other sources. This could be difficult if management takes a view that is contrary to consensus views."**
Discover Financial Services: Comment Letter No. 180
"We generally agree with the idea of incorporating within an estimate of expected credit losses reasonable and supportable forecasts that affect the expected collectability of the financial assets. However, we think this should be limited to a reasonably foreseeable future as doing so will provide the most reliable information and will better balance the costs and benefits of incorporating a forward-looking forecast into the loss estimate. As already noted, a **lifetime loss estimate for long-lived financial instruments, including assumptions about future economic conditions and trends, would be inherently unreliable**. **This lack of reliability could create earnings volatility that stems from revisions to assumptions over time as opposed to actual changes in credit risk. Such results would not be a faithful representation of credit performance and therefore would undermine the goal of providing the most decision-useful information.** As part of the forward-looking considerations required under the model, the proposal requires the loss estimate to include an evaluation of both the current point in, and the forecasted direction of, the economic cycle. **We believe it will be very difficult for most entities to make this economic assessment, and it is likely that this inability will create less comparability between institutions.** Even if an accurate assessment of the economic cycle could be made, it would be challenging to support reserve changes that are at odds with prevailing economic conditions."

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