Imperfect Expectations in Loan Loss Forecast*

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Abstract

Loan loss forecasts that deviate from rational expectations can impact banks' loan loss provisions, lending procyclicality, and financial stability, especially under the forward-looking current expected credit losses (CECL) model. The behavioral finance literature suggests that bank forecasts are influenced by the representativeness heuristic, which posits that, in forming estimates of future events, forecasters overreact to the circumstances that they are currently experiencing. Leveraging confidential supervisory data from FR Y-14A filings, we document the presence of such overreaction in banks' loan loss forecasts. We find that revisions of net loan charge-off (NLCO) forecasts (current forecast minus previous forecast) are negatively associated with the corresponding forecast errors (actual minus current forecast), and this pattern strengthens for longer-horizon forecasts. Successive forecasts targeting the same future NLCO exhibit negatively autocorrelated revisions and gradually converge to the realization, indicating the continued presence and gradual resolution of overreaction over time. The overreaction affects loan loss provision in the same direction as the forecast bias, especially for CECL adopters. The effect of overreaction under CECL is more pronounced for longer-horizon forecasts and banks with longer-maturity loans. Supporting the robustness and prevalence of this bias in bank forecasts, we observe overreaction in loan loss forecasts across loan types and in forecasts of regional macroeconomic conditions.

Keywords: Loan loss forecast, representativeness heuristic, overreaction, banks, CECL.

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1. Introduction

Forecasts of future loan losses are central to banks' loan loss recognition. The quality of these forecasts, driven by factors such as credit risk models, information, and sentiment, affects the timeliness of banks' loan loss provisions (Bhat, Ryan, and Vyas, 2019; Balakrishnan and Ertan, 2021; Yang, 2022; Hribar, Melessa, Small, and Wilde, 2017). The impact of bank forecast quality is amplified by the introduction of the current expected credit losses (CECL) standard, which requires banks to recognize lifetime expected credit losses. Systematic errors in expectation formation are an important factor that can shape banks' forecast quality. Specifically, the behavioral finance literature suggests that lenders and their investors are influenced by Kahneman and Tversky's (1972) representativeness heuristic, overreacting to recent events in making lending and investment decisions (Barron and Xiong, 2017; Bordalo, Gennaioli, and Shleifer, 2018; Fahlenbrach, Prilmeier, and Stulz, 2018). This overreaction is considered to impair banks' ability to anticipate turns in economic cycles, exacerbating lending procyclicality and systemic risk, especially under CECL (Ryan, 2019; Chen, Dou, Ryan, Zou, 2025; Vidinova, 2024). Despite the importance of this behavioral bias, no prior study directly documents the presence of the representativeness heuristic in banks' forecasts, potentially due to data limitations. To fill this gap, we provide evidence consistent with this heuristic using confidential supervisory data on banks' forecasts. Further, we examine the resolution of the overreaction over the life of the forecast and the effect of the overreaction on loan loss provisions, especially with the introduction of CECL.

Economic agents influenced by the representativeness heuristic tend to overreact to recent events and overestimate the likelihood that future outcomes will resemble those they are currently experiencing (Kahneman and Tversky, 1972, 1974).[1] For example, an economic boom (downturn) can give rise to overly optimistic (pessimistic) expectations of future economic conditions, leading to underestimated (overestimated) future loan losses. This overreaction has been observed in the forecasts of various economic agents, including analysts, professional macroeconomic forecasters, securitization professionals, and students from elite universities (Cheng, Raina, and Xiong, 2014; Bordalo, Gennaioli, Ma, and Shleifer, 2020; d'Arienzo, 2020; Afrouzi, Kwon, Landier, Ma, and Thesmar, 2023; Bordalo, Gennaioli, La Porta, O'Brien, and Shleifer, 2024). These studies predominantly focus on individuals. With the notable exception of Andonov and Rauh (2022), who document the presence of overreaction in pension funds' forecasts, there is little evidence of this bias at the institutional level. Although group-level decision-making does not always correct for individual-level biases (Kerr, MacCoun, and Kramer, 1996), it remains an open question whether bank forecasts are influenced by the representativeness heuristic, especially considering their sophisticated internal models, extensive datasets, refined forecasting processes, and rigorous regulatory oversight.

To examine systematic errors in banks' loan loss forecasts, we focus on net loan charge-off forecasts, as they are directly connected to credit risk assessment and loan loss provisions.[2] Additionally, we examine macroeconomic forecasts, as they are a key input for loan loss predictions. We obtain data on large banks' forecasts submitted to the Federal Reserve as part of their Comprehensive Capital Assessment and Review (CCAR) requirements and the Dodd-Frank Act Stress Testing (DFAST) requirements of the Office of the Comptroller of the Currency. Under

[1] For reviews on the applications of the representativeness heuristic in various fields of research, see Malmendier (2018) for corporate finance, Barberis (2018) for asset pricing, and Benjamin (2019) for economics.

[2] We sometimes refer to "net loan charge-offs" using the term "loan losses" in the paper for simplicity. Allowances and provisions for loan losses are accrual measures of loan losses, and we refer to these accrual measures only using terms that include "allowance" or "provision."

DFAST and CCAR, all large banks with total assets above $250 billion (known as Category I, II, and III banks) must submit FR Y-14 Schedule A reports (FR Y-14A). These reports include forecasts of key balance sheet, income statement, and capital items, as well as metropolitan statistical area (MSA)-level macroeconomic conditions, for each of the next nine quarters (77 FR 62417). Covered banks generate four versions of forecasts, using baseline scenarios defined by the banks and the Federal Reserve, as well as stress scenarios defined by these two parties. We use forecasts based on banks' chosen baseline scenarios for our analysis, as these forecasts are derived from banks' own expectations of the most likely economic conditions, making them the closest representation of banks' beliefs about future performance. The data available to us covers all 22 stress test banks regulated by both the Fed and the OCC from 2014 to 2022.

The FR Y-14A data offers several advantages for our study. First, the data includes forecasts of net loan charge-offs and loan amounts for one to nine quarters ahead. Therefore, we can measure forecasts of the net loan charge-off rate, NLCO (i.e., the ratio of net loan charge-offs to average loan amount), and match them with future realizations and previous forecasts to calculate NLCO forecast errors and forecast revisions. Second, the data includes banks' macroeconomic forecasts at the MSA level, which allow us to examine overreaction in the forecasts of key inputs for NLCO forecasts with a tight fixed effects structure, providing further support to our main findings. Third, the CCAR/DFAST forecasts are not published and thus not subject to market pressures. In addition, since stress test results are primarily determined by the stress scenario forecasts, the baseline forecasts we use are subject to low regulatory pressure. Fourth, regulators closely scrutinize the quality of banks' CCAR/DFAST forecasts. Overall, these features facilitate the analysis of bank forecasts using high-quality data.

In our baseline analysis, we examine the association between forecast revisions and forecast errors, following prior research (Coibion and Gorodnichenko, 2012, 2015; Bouchaud et al., 2019; Bordalo et al., 2020; d'Arienzo, 2020; Afrouzi et al., 2023; Bordalo et al., 2024c). Forecast error is calculated by subtracting the predicted number from the corresponding realized value, while forecast revision is calculated by subtracting the previous forecast from the current one for the same future target quarter. Under rational expectations, the two measures should be uncorrelated, as forecast revisions made in time t (i.e., forecast made in t minus forecast made in t-1, both for t+1 realization) should have no predictive power for forecast errors determined by the realization in t+1 (i.e., actual in t+1 minus forecast made in t for t+1 realization). A negative association between forecast revisions and forecast errors suggests that forecast revisions tend to be followed by realizations that deviate from the revised forecast in the opposite direction of the revision (e.g., predicting an increase in NLCO is followed by a realization that is below the predicted NLCO), indicating overreaction in forecasts relative to the rational benchmark.

Consistent with the presence of overreaction, our baseline regression reveals a significant negative association between banks' NLCO forecast revisions and forecast errors. This negative association strengthens for longer-term forecasts, a pattern observed in recent studies examining overreaction in various settings (e.g., Giglio and Kelly, 2018; Bordalo et al., 2020, 2024a,b; d'Arienzo, 2020; Angeletos, et al., 2020). In exploring the resolution of overreaction, we find that successive forecast revisions targeting the same future NLCO are negatively autocorrelated, with the absolute value of the autocorrelation coefficient less than one. This pattern indicates that forecast revisions overreact to new information as it arrives, but the overreaction gradually resolves over successive updates, converging the forecasts to the realized NLCO. These results remain robust to alternative specifications that include or exclude various fixed effects.

If the overreaction influences banks' credit risk assessment, it should affect their loan loss provisions. Moreover, since the bias is more pronounced in longer-term forecasts, its impact on provisions should be especially significant under CECL, which requires more forward-looking provisioning. Indeed, we find that overreaction in NLCO forecasts leads to corresponding shifts in loan loss provision (LLP) in the same direction as the forecast bias, with the effect concentrated among CECL-adopting banks. This result supports the view that banks' limited ability to forecast cycle turns leads to increased procyclicality under CECL (Ryan, 2019; Chen et al., 2025) and suggests that the representativeness heuristic underlies this inability. In addition, we find that the impact of overreaction in NLCO forecasts on LLP among CECL adopters is more pronounced for longer-horizon forecasts and for banks holding loans with longer maturities. These findings are consistent with the increased influence of longer-term forecasts, and hence their overreaction, on LLP under CECL. They also point to a behavioral force contributing to CECL's greater impact on banks with longer-maturity loans, as documented in prior research (Granja and Nagel, 2025).

We conduct additional analyses to test the robustness and prevalence of overreaction in bank forecasts. First, we separately examine NLCO forecasts for real estate, commercial and industrial (C&I), and consumer loans, and find consistent negative associations between forecast errors and revisions for all three loan types. Second, we provide evidence that our main finding cannot be explained by the unexpected impact of the COVID-19 pandemic on the forecasts made immediately before it. Third, we find evidence of overreaction in banks' MSA-level house price index (HPI) forecasts, a key input for loan loss forecasts, even with a tight fixed effect structure at the MSA-year-quarter and bank-year-quarter levels. This finding aligns with Ryan's (2019) and Chen et al.'s (2025) argument that inaccurate macroeconomic forecasts may amplify procyclicality. Finally, we find that overreaction in HPI forecasts is more pronounced for MSAs where the forecasting bank has a significant branch presence. This result is consistent with findings in prior research that forecasts overreact more to information about assets owned by the forecasters, as they pay closer attention to relevant information (Hartzmark, Hirshman, and Imas, 2021).

Our paper contributes to the literature in several ways. First, it contributes to the literature on the financial reporting and regulation of banks' expected credit losses (Beatty and Liao, 2014; Acharya and Ryan, 2016). Prior studies suggest that factors affecting the quality of loan loss forecasts influence the timeliness of banks' loan loss recognition (Bhat et al., 2019; Balakrishnan and Ertan, 2021; Yang, 2022; Hribar et al., 2017). These forecasts play an even greater role after the adoption of CECL. In particular, Ryan (2019) and Chen et al. (2025) argue and provide evidence that the adoption of CECL can lead to more procyclical loan loss provisions and lending due to banks' inability to predict cycle turns. Vidinova (2024) further illustrates in a theoretical model that this inability can stem from the influence of the representativeness heuristic on bank forecasts. Our paper provides empirical evidence that supports these arguments. In addition, we offer novel insights that complement Granja and Nagel's (2025) recent finding of CECL's greater impact on banks with longer-maturity loans.

Second, the paper contributes to the growing body of positive accounting research grounded in behavioral economics (as surveyed by Hanlon, Yeung, and Zuo, 2022), which emphasizes that individual characteristics—such as non-standard preferences and deviations from Bayesian beliefs—can shape observed accounting practices. Our work extends this literature by documenting how the representativeness heuristic, a non-Bayesian belief formation process, affects banks' loan loss forecasts, a key component in their financial reporting. By linking a behavioral factor to loan loss provisions and the effect of CECL on these provisions, our paper answers Hanlon et al.'s (2022) call to treat the "people dimension with equal importance as other economic dimensions" in explaining accounting phenomena.

Finally, our paper adds to the literature on the role of behavioral biases in credit cycles. This literature demonstrates that the representativeness heuristic is a key mechanism underlying credit cycles and financial crises (Mian and Sufi, 2009; Schularick and Taylor, 2012; López-Salido, Stein, and Zakrajšek, 2017), with implications for the design of optimal crisis-prevention policies (Fontanier, 2025). Our finding that banks' NLCO forecasts are subject to this heuristic aligns with this line of research and behavioral (rather than agency) explanations for financial crises. Therefore, our paper echoes the call to "expand the incentives-based view of the [financial] crisis to incorporate a role for beliefs" (Cheng et al., 2014; Gennaioli and Shleifer, 2018).

2. Literature, hypothesis, and background

2.1 Loan loss forecasts and provisions

Predicting future loan losses is an integral part of banks' accrual estimation of loan losses. Prior research provides evidence that factors affecting the quality of loan loss forecasts influence loan loss provision decisions. For example, findings in Bhat et al. (2019) suggest that better credit risk modeling improves banks' credit risk assessment, resulting in timelier and more forward-looking loan loss provisions. Balakrishnan and Ertan (2021) and Yang (2022) find that the quantity and quality of information banks use to assess credit risk are positively associated with the timeliness of their loan loss recognition. Hribar et al. (2017) find that aggregate sentiment from public and private companies across industries is negatively associated with banks' loan loss provisions. Prior research further shows that the timeliness of loan loss recognition, in turn, influences banks' credit allocation and ultimately financial stability (Beatty and Liao, 2011;

Bushman and Williams, 2015). Loan loss forecasts become even more important after the adoption of the current expected credit losses standard (CECL), which requires banks to recognize lifetime expected credit losses and incorporate macroeconomic forecasts into their loan loss provisions. The new standard prompted banks to collect more forward-looking information (Kim, Kim, Kleymenova, and Li, 2023) and raised researchers' interest in examining loan loss forecasts (Harris, Khan, and Nissim, 2018; Wheeler, 2021; Lu and Nikolaev, 2022). More recently, Granja and Nagel (2025) find that CECL adoption increases loan interest rates, especially for longer-maturity loans.

Importantly, banks' ability to predict loan losses influences the effect of CECL on lending procyclicality. While CECL aims to reduce procyclicality in provisioning and lending by requiring banks to front-load loss recognition, it extends the horizon for loss recognition and hence can exacerbate the procyclicality. As pointed out by Ryan (2019) and Chen et al. (2025), the second force is likely to dominate the first if banks cannot accurately predict cycle turns, i.e., predicting good (bad) future outcomes in currently bad (good) conditions. Existing evidence suggests that professional forecasters and macroeconomic models generally fail to accurately predict cycle turns (Covas and Nelson 2018; Ryan 2019). They tend to expect the continuation of recent macroeconomic trends without adequately adjusting to the early signals of cycle shifts, leading to increased procyclicality under CECL. This tendency to overreact to recent experience is consistent with the influence of the representativeness heuristic in forecasts. Recent theoretical work by Vidinova (2024) also highlights this heuristic as a source of procyclicality under CECL.

2.2 Representativeness heuristic in bank forecasts

How financial institutions form their beliefs and forecast performance has emerged as an increasingly important research area following the financial crisis (Sufi and Taylor, 2022). A growing body of literature demonstrates that credit expansions are predictably followed by adverse outcomes such as increased mortgage defaults, declines in real activity, and financial crises (Mian and Sufi, 2009; Schularick and Taylor, 2012; López-Salido et al., 2017; Mian, Sufi, and Verner, 2017; Greenwood, Hanson, Shleifer, and Sørensen, 2022). In the banking sector specifically, rapid credit expansion is associated with riskier loan portfolios, lower bank equity returns, and poorer subsequent loan performance (Barron and Xiong, 2017; Fahlenbrach et al., 2018). This suggests that when forming expectations during periods of rapid credit growth, banks, their shareholders, and analysts do not adequately account for predictable signals of risk.

The extensive and robust evidence that credit expansions lead predictably to subsequent recessions and crises challenges traditional theories based on rational expectations (e.g., Bloom et al., 2018; Arellano et al., 2019). This discrepancy "brings behavioral biases to the forefront when considering the boom-bust cycle associated with financial crises" (Sufi and Taylor, 2022). Several behavioral finance theories on this topic have been developed based on Kahneman and Tversky's (1972) representativeness heuristic, a cognitive shortcut where individuals estimate the probability of an event based on how similar it is to a known prototypical event. These models have been shown to explain credit cycles and key phenomena surrounding financial crises (Bordalo et al., 2018; Maxted, 2024; Bordalo et al., 2024b; Bianchi, Ilut, and Saijo, 2024; L'Huillier, Singh, and Yoo, 2024). These theories predict that banks overreact to recent events when making forecasts. Specifically, positive (negative) circumstances lead to overly optimistic (pessimistic) expectations of future loan performance, resulting in underestimated (overestimated) future loan losses. While empirical evidence from the credit cycle literature is consistent with this theoretical prediction, no study has directly examined the presence of this overreaction in banks' forecasts.

Outside the banking sector, such direct evidence has been documented in empirical studies examining the forecasts by various types of economic agents, including investors, analysts, professional macroeconomic forecasters, securitization professionals, credit officers, and students from elite universities (Da, Huang, and Jin, 2021; Bordalo et al., 2024a; Bordalo et al., 2020; d'Arienzo, 2020; Cheng et al., 2014; Liu, 2022; Afrouzi et al., 2023). However, whether such findings for individuals can be directly applied to the banking context is unclear. On the one hand, extensive evidence suggests that decision-making at the group level often does not correct for individual-level biases (Kerr et al., 1996). Indeed, Andonov and Rauh (2022) document the presence of overreaction in pension funds' forecasts. On the other hand, large banks' sophisticated internal models, extensive datasets, refined forecasting processes, and rigorous regulatory oversight might mitigate or even eliminate overreaction in their forecasts. Consequently, whether the representativeness heuristic contributes to banks' forecast errors remains an open question, and we hypothesize that banks' NLCO forecasts are subject to the representativeness heuristic.

2.3. Stress testing forecasts

In response to the 2007-2009 financial crisis, the Federal Reserve introduced its Comprehensive Capital Adequacy and Review (CCAR) requirements in 2011, requiring large bank holding companies (BHCs) to conduct comprehensive assessments of their ability to meet capital requirements under alternate stress scenarios (76 Fed. Reg., no 231, 74631-74648; 2011). The same year, the Office of the Comptroller of the Currency issued Dodd-Frank Act Stress Testing (DFAST) requirements effective for the larger banks they regulate (OCC 2011-0029). Since the introduction of CCAR and DFAST, the requirements have changed from time to time. The coverage of banks has also changed, with some smaller banks being exempted from certain requirements in recent years. However, Category I, II, and III banks (categorized by the Final Tailoring Rules and representing banks with total assets above $250 billion) are required to provide regulators with detailed financial projections of their balance sheet, income statement, and capital calculations at the bank holding company level, as well as forecasts of regional macroeconomic conditions, over nine quarters under alternate scenarios provided by the Federal Reserve and under their own selection of baseline and stress scenarios. Regulated banks need to submit these projections to regulators through FR Y-14 Schedule A (FR Y-14A). This data is confidential and not publicly released. The stress tests and the corresponding forecasts are typically conducted annually with the year-end as the last quarter before the start of the projection horizon (except for 2014, when the forecast was made at the end of September). Some banks also made mid-year forecasts at the end of June (always over nine quarters ahead) during 2015-2018 due to changes in stress test requirements over the sample period.[3]

The FR Y-14A filings include forecasts generated using two sets of scenarios: (1) supervisory scenarios that are provided annually by the Federal Reserve and (2) banks' own scenarios. Each of these comprises baseline and stress scenarios.[4] The baseline scenarios reflect "more likely economic and financial conditions," while stress scenarios assume a significantly more adverse economic environment (77 FR 62391). Forecasts generated by the Federal Reserve are based on assumptions and methodologies that it develops and are used for "Fed-run" supervisory stress tests. In contrast, forecasts generated by banks, which are used for "company-run" stress tests, are based on their assumptions and methodologies. While using their scenarios, banks generate projections for key macroeconomic variables, such as the house price index and

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[3] The larger (Category I, II, and III) banks continued to provide mid-year forecasts until 2020. After 2020, these banks update their forecasts at least once a year. Since 2018, Category IV banks (banks with total assets between $100 and $250 billion) are no longer required to submit forecasts. Therefore, for some banks in our database, the last forecast date is June 2018.

[4] The initial rule includes three scenarios: baseline, adverse, and severely adverse. The adverse scenario was removed from the list of required scenarios in 2019 following the Economic Growth, Regulatory Relief, and Consumer Protection Act (EGRRCPA). We refer to both adverse and severely adverse scenarios as "stress scenarios" in this paper.

GDP growth.[5] In this process, banks often need to model loan losses using more granular predictors (e.g., MSA-level house price indices), in which case they have to determine the appropriate mapping of high-level predictions (e.g., national house price index) to these predictors under their company-generated baseline scenario. We expect financial projections based on banks' baseline scenarios to be most likely to reflect their actual expectations of future performance, and so we use these forecasts in our analysis.

Several features of bank-generated baseline forecasts make them well-suited for our study. First, regulated banks forecast quarterly financial statement items that can be matched directly to their corresponding financial statement numbers. Specifically, predicted loan losses account not only for existing loans but also for future changes in loan balances from new issuance and the sale or retirement of existing loans. This allows us to calculate forecast errors by subtracting predicted NLCOs from realized NLCOs. Because the forecasts span nine future quarters, we can calculate forecast revisions by comparing the current year's one- to five-quarter-ahead forecasts with the previous year's five- to nine-quarter-ahead forecasts. While banks' financial reports contain forward-looking loan loss measures, such as the allowance for loan losses or loan loss provisions, these measures cannot be used to estimate forecast errors or revisions because they do not capture expected changes in underlying loan balances in the future.

Second, banks' macroeconomic forecasts at the regional level enable us to examine overreaction in these forecasts. Specifically, our data includes predictions of the house price index (HPI) for each metropolitan statistical area (MSA) by a subset of our sample banks from 2017 to

[5] Banks must use Fed-provided scenarios as a basis to generate their own scenarios in company-run stress tests. In practice, they typically adjust the Fed's scenarios by incorporating their own predictions. In addition, banks generate macroeconomic forecasts using either their in-house models or forecasts provided by third-party vendors (which can be further adjusted by the bank).

2022.[6] These banks report the corresponding realized HPI in the forecasting quarters, allowing us to calculate HPI forecast errors using banks' reported realized and predicted values.[7] Because we have observations of forecasts made at both mid-year and year-end, we can obtain realized HPI data to calculate both two- and four-quarter-ahead forecast errors. We match these forecast errors with the corresponding forecast revisions to examine overreaction in banks' HPI forecasts.

Third, because the baseline forecasts are not publicly disclosed, the forecasted numbers are not subject to reporting incentives that affect publicly reported accounting numbers (e.g., Ball, Robin, and Wu, 2003; Burgstahler, Hail, and Leuz, 2006; Bischof, Laux, and Leuz, 2021). Meanwhile, banks also do not face strong regulatory pressures to "window dress" the company-run baseline forecasts, because their capital requirements are computed using the Fed-run stress scenarios. Consistent with this view, Ma, Paligorova, and Peydro (2022) find that banks with weaker balance sheets (which have stronger incentives to window dress) are not more optimistic in their CCAR/DFAST forecasts of GDP growth and that these forecasts also align with their forecasts reported to other data providers (e.g., Blue Chip). Even in stress scenario forecasts, where regulatory pressure might encourage banks to be pessimistic, prior research fails to find evidence that these forecasts are pessimistic (Agarwal et al., 2024).

Fourth, bank supervisors closely scrutinize the processes used to generate CCAR/DFAST forecasts to ensure their quality, as these forecasts form the basis of company-run stress tests. Bank examiners conduct thorough evaluations of the methodologies, models, assumptions, and data used

[6] We focus on MSA-level HPI because it is the most frequently predicted regional macroeconomic factor in our sample.
[7] Using HPI from other data providers is problematic because there are multiple versions of HPI, and banks often do not specify which one they use in their forecasts. The three most common versions of HPI are CoreLogic HPI, CoreLogic Case-Shiller HPI, and the HPI from the Federal Housing Finance Agency (FHFA). Moreover, CoreLogic HPI and CoreLogic Case-Shiller HPI are subject to retrospective revisions for up to 60 and 24 months, respectively, after the initial measurement if there are future home sales. For example, the value of the January 2017 CoreLogic HPI in an MSA can be updated after a home sale in that MSA in December 2022.

in generating these forecasts, ensuring that banks develop these forecasts in a rigorous and consistent manner. However, bank supervisors also allow banks to incorporate their expectations into projecting future performance, as discussed above.[8] This leaves room for errors in banks' expectations to affect the final forecasted numbers. In addition, bank supervisors evaluate the accuracy of numeric forecasts based on their deviation from realized values using metrics such as the root mean square error (RMSE), and they do not treat forecast errors resulting from overly pessimistic predictions as more favorable. As a result, banks do not tend to face more scrutiny or punishment for being too optimistic rather than conservative in their forecasts.

Finally, even if banks were to face regulatory pressure to be overly pessimistic, this tendency itself does not explain the negative association between forecast error and forecast revision. The pressure needs to intensify following worse news for one to observe more pessimistic forecasts in response to such news, an overreaction pattern predicted by the representativeness heuristic. However, regulators are unlikely to favor even more pessimistic forecasts during market downturns or crises. Such over-pessimism can lead to excessive lending cuts, liquidity hoarding, and panic, ultimately amplifying systemic risk. In conclusion, our data allows us to observe high-quality bank forecasts and examine the presence of overreaction in these forecasts.[9]

3. Empirical design

3.1 Measurement

We define two key measures for our analysis—loan loss forecast error and loan loss forecast revision—following prior research (Coibion and Gorodnichenko, 2015; Bordalo et al.,

[8] For more details of supervisory model reviews, please see The Fed - Supervisory Letter SR 12-17 / CA 12-14 on Consolidated Supervision Framework for Large Financial Institutions -- December 17, 2012.
[9] Institutional details on CCAR/DFAST forecasts discussed in this subsection are based on our conversations with bank examiners and regulators.

2020, 2024a,b; Afrouzi et al., 2023). First, we calculate a bank's loan loss forecast error as its net loan charge-off rate (NLCO) in a future quarter minus the predicted NLCO for that quarter. NLCO is net loan charge-offs scaled by average loans outstanding. Because banks predict their performance for each of the nine quarters in the future, we can calculate nine forecast errors each time a bank makes forecasts. Formally, we define h-quarter-ahead loan loss forecast error, *NLCO_Error*, as:

$$NLCO\_Error_{i,t,h} = NLCO_{i,t+h} - NLCO\_Pred_{i,t,h} \quad (1)$$

The subscript *i* represents the bank that makes the forecast, *t* represents the year-quarter the bank makes the forecast, and *h* (*h* =1, 2, 3, …, or 9) represents the forecast horizon in quarters. $NLCO_{i,t+h}$ is net loan charge-offs in the h^{th} quarter after *t*, scaled by the average of total loans outstanding at the end of *t*+*h* and *t*+*h*-1. $NLCO\_Pred_{i,t,h}$ is the predicted net loan charge-offs made in *t* for the h^{th} quarter after *t*, scaled by the average of predicted total loans outstanding at the end of *t*+*h* and *t*+*h*-1.

Second, we calculate a bank's loan loss forecast revision as the most recent forecast for a given future quarter's NLCO minus the corresponding forecast made four quarters ago. Since the two forecasts are made four quarters apart and each forecast spans nine quarters into the future, we can calculate five forecast revisions each time a bank makes new forecasts, with the last one being the current forecast for the fifth quarter in the future minus the previous forecast for the ninth quarter in the future. Formally, we define h-quarter-ahead forecast revision, *NLCO_Rev*, as:

$$NLCO\_Rev_{i,t,h} = NLCO\_Pred_{i,t,h} - NLCO\_Pred_{i,t-4,h+4} \quad (2)$$

h =1, 2, 3, …, or 5.

Similarly, we calculate the errors and revisions for banks' MSA-level HPI forecasts. As in the case of NLCO forecasts, we can calculate one- to five-quarter-ahead HPI forecast revisions each time a bank makes new forecasts. Unlike NLCO forecasts, however, we can only match these forecast revisions with forecast errors of two- and four-quarter-ahead actual HPI. As discussed in Section 2.3, this is because we use the HPI values banks report in the forecasting quarters to calculate forecast errors, and banks make HPI forecasts only in the second or fourth quarter.

3.2 Model specification

The presence of the representativeness heuristic can be tested by examining the association between banks' forecast errors and forecast revisions. Earlier behavioral studies have documented links between analysts' forecast revisions and subsequent errors (e.g., DeBondt and Thaler, 1990; Chaney et al., 1999). Coibion and Gorodnichenko (2015) integrate this relation into a formal expectation-formation framework: under rational expectations, revisions should be uncorrelated with future errors because all available information is already incorporated.[10] In contrast, a negative coefficient, where upward (downward) revisions tend to be followed by lower(higher)-than-expected outcomes, signals overreaction relative to the rational benchmark, consistent with the representativeness heuristic. This revision-error test has since been applied in various contexts (e.g., Bouchaud et al., 2019; Bordalo et al., 2020; d'Arienzo, 2020; Afrouzi et al., 2023; Bordalo et al., 2024b) to document biased expectation updating. Formally, we examine our main hypothesis by running the following regression:

$$NLCO\_Error_{i,t,h} = \beta_0 + \beta_1 NLCO\_Rev_{i,t,h} + \alpha_i + \alpha_t + \alpha_h + \epsilon_{i,t} \quad (3)$$

NLCO_Error and *NLCO_Rev* are NLCO forecast errors and revisions (over prior year), as defined in Section 3.1. h =1, 2, 3, …, or 5. The dependent variable is constructed over five separate

[10] Strictly speaking, rationality requires that forecast revisions be mean independent of future forecast errors (i.e., E[error | revision] = E[error]), which is a stronger condition than uncorrelatedness (Cov(error, revision) = 0). In the empirical behavioral literature, testing for zero correlation is a practical and tractable proxy for mean independence under common distributional assumptions.

horizons and then pooled. We include bank fixed effects, α_i, to control for time-invariant bank characteristics, year-quarter-fixed effects, α_t, to control for general time trends, and forecast horizon fixed effects, α_h, to control for variations driven by the difference in forecast horizons.

Including bank fixed effects allows us to absorb time-invariant, unobserved bank characteristics, such as management style, internal controls, or risk appetite, that could otherwise drive both forecast revisions and forecast errors. For instance, a bank with rigorous governance may tend to issue upward (more cautious) NLCO revisions throughout the sample period and thus record negative errors, whereas a bank inclined toward risk-taking might issue downward revisions and show positive errors. Without bank fixed effects, our estimated coefficient could conflate these persistent cross-sectional differences with the within-bank overreaction to new information. However, we recognize that including bank fixed effects might affect the magnitude of coefficient estimates (Breuer and deHaan, 2024), as it can strip out meaningful cross-bank differences in the average level of overreaction in NLCO forecasts. To mitigate this concern, we also report results from specifications omitting bank fixed effects to demonstrate robustness.

Including time fixed effects helps purge the influence of common shocks. Consider a scenario where a gradually worsening macroeconomic trend up to time *t* leads to steadily positive NLCO revisions (i.e., more pessimistic outlooks) issued by all banks at time *t*. At time *t*+1, however, a macroeconomic shock (e.g., an economic relief package) reverses this pattern and leads to a decline in NLCO across the banking sector, resulting in negative forecast errors for all banks. Without time fixed effects, these events would mechanically generate a negative association between forecast revisions and forecast errors. Removing this mechanical association using time fixed effects is particularly relevant for our setting, as we have a short sample period, and a few one-off shocks could significantly distort our estimates. However, because macro shocks at time

t+1 are precisely the kind of new information banks should incorporate into their forecast revisions made at t+1, absorbing all common macro shocks risks "throwing out the baby with the bathwater." Consequently, we also present results without time fixed effects.

Following the same approach as in Model (3), we examine the representativeness heuristic in banks' forecasts of MSA-level HPI using data at the bank-year-quarter-MSA level. We run the following regression:

$$HPI\_Error_{i,t,m,h} = \beta_0 + \beta_1 HPI\_Rev_{i,t,m,h} + \alpha_{i,t} + \alpha_{m,t} + \alpha_h + \epsilon_{i,t} \quad (4)$$

HPI_Error and *HPPI_Rev* are HPI forecast errors and revisions (over prior year), as defined in Section 3.1. h = 2 or 4, as explained in Section 3.1. m stands for MSA. The more granular HPI forecast data allows us to adopt a stricter fixed effect structure. We include MSA-year-quarter fixed effects, $\alpha_{m,t}$, to compare banks operating in the same MSA and at the same time, eliminating the effect of common local shocks at the MSA-year-quarter level. While including these fixed effects removes the effect of ex ante local shocks in inducing overreaction in forecasts, findings without these fixed effects can be driven by local economic shocks that mechanically generate negative associations between forecast revisions and forecast errors (e.g., positive NLCO forecast revisions followed by local economic shocks that lead to overestimated NLCO in certain MSAs). We also include bank-year-quarter fixed effects, $\alpha_{i,t}$, to compare across MSAs for the same bank at the same time, controlling for the influence of time-varying bank characteristics. While including these fixed effects removes the effect of bank-specific shocks that induce overreaction in forecasts, this design mitigates the concern that our results can be driven by regulatory pressure and other forces that operate at the bank-year-quarter level, such as intensified scrutiny of weaker banks during crisis periods. With this fixed effect structure, confounding economic shocks and their subsequent reversals at the MSA level or omitted time-varying bank characteristics, such as time-varying risk appetite or regulatory pressure, are unlikely to explain our results.

4. Data

The data on bank holding companies' financial and macroeconomic projections are from the FR Y-14 Schedule A (FR Y-14A) reports, as discussed in more detail in Section 2.3. The data available to us covers all 22 banks subject to the CCAR and DFAST stress testing requirements and regulated by both the Fed and the OCC. The data is at the holding company level from 2014 to 2022. We complement the forecast data with financial data from banks' publicly available FR Y-9C reports and branch location data from the Federal Deposit Insurance Corporation's (FDIC) Summary of Deposits database. To mitigate the influence of extreme observations, we winsorized all continuous variables at their 1st and 99th percentiles.

5. Results

5.1 Descriptive evidence of forecast errors

We begin by providing descriptive evidence about banks' NLCO forecast errors. Table 1 reports the summary statistics with all ratios expressed in percentages (i.e., multiplied by 100) for ease of interpretation. The median forecast error of net loan charge-offs (*NLCO_Error*), across all banks during the sample period for all forecast horizons, equals a nontrivial 0.018% of average loans, and around 24% of the median NLCO. Banks' forecasts tend to be pessimistic, as indicated by the negative mean and median of forecast errors. Furthermore, there is considerable variation in NLCO forecast accuracy, indicated by a standard deviation of 0.08%, and a notable difference between the 25th percentile (-0.0478%) and the 75th percentile (-0.0029%). This variation can arise from several sources, including overreaction in bank forecasts, forecast noise, and macroeconomic shocks. We formally test the role of overreaction in our main analysis. Forecast error of HPI (*HPI_Error*) displays substantial variation as well, with its standard deviation nearly twice as large as its mean value.

Banks regularly adjust their expectations for future NLCOs, as evidenced by their revisions in net loan charge-off forecasts (*NLCO_Rev*). As Table 1 shows, these revisions exhibit a magnitude of variation similar to that of *NLCO_Error*, indicating that banks meaningfully update their NLCO expectations over time, likely in response to new information. Revisions of HPI also display significant variation, as evidenced by their standard deviations and interquartile ranges, which are of similar magnitude to their corresponding forecast errors.

In Figure 1, we plot banks' NLCO forecast errors, averaged across banks and forecast horizons, over time (from 2014 to 2022). Average forecast errors are negative over all our sample years and drop sharply for forecasts made in 2019 and 2020.[11] The drop is likely driven by the disruption of the COVID-19 pandemic, though through different channels. The negative 2019 forecast errors are likely due to the unexpected shock from the pandemic in 2020 and almost immediate Federal Reserve interventions that lowered loan losses. This is unlikely to explain the even more negative 2020 forecast errors, as the pandemic and related interventions were widely known when the forecasts were made in 2020 (forecasts are mostly made at year-end, with some also made at mid-year). Instead, the 2020 forecast errors are more likely to reflect banks' ex-post overly pessimistic expectations regarding future loan losses in response to the pandemic shock. The much more negative forecast errors in 2020 compared to 2019 suggest that ex-post overreaction in bank forecasts might play a central role in the overall impact of the pandemic shock on banks' forecast errors. We formally test for this overreaction later in the paper. Figure 2 plots

[11] We observe similar patterns when plotting the figure for each forecast horizon separately (untabulated).

the average loan loss forecast errors for forecast horizons ranging from one to nine quarters ahead. We observe that forecast errors become more negative as the forecast horizon increases, which suggests that longer-term loan losses may be more challenging to predict.

We conduct two additional tests on NLCO forecasts to motivate our main analysis. First, as reported in Table OA1 in the online appendix, NLCO forecast revisions are significantly positively associated with loan loss provisions, while forecast revisions of other performance metrics, including the Tier 1 capital ratio, return on assets (ROA), and core deposits, have limited explanatory power. These results suggest that, despite the non-trivial errors in NLCO forecasts, banks rely on these forecasts to provision for loan losses. Therefore, it is important to examine the determinants of these errors and their impact on banks' loan loss provisioning. Second, as reported in Table OA2, NLCO forecast errors are insignificantly related to credit risk-related bank characteristics, including lagged NLCO, bank size, capital, loan rates, loan durations, and loan types. Notably, larger and better capitalized banks do not produce smaller forecast errors, suggesting that factors such as banks' capabilities, resources (captured by size), or agency frictions (captured by capital ratio) play a limited role in determining forecast accuracy. Overall, the weak explanatory power of bank characteristics leaves room for the importance of systematic biases in banks' loan loss forecasts, which we explore next.

5.2 Representativeness heuristic in loan loss forecasts

In this section, we conduct a series of analyses guided by the behavioral finance literature to investigate the influence of the representativeness heuristic on banks' loan loss forecasts. In our baseline analysis, we regress banks' NLCO forecast errors on forecast revisions, following Model (3) in Section 3.2. Our findings, presented in Table 2, are consistent with the presence of overreaction in banks' loan loss forecasts. As reported in Column 1, forecast errors are significantly negatively correlated with forecast revisions. In addition, the coefficient's magnitude (0.5372) is in line with similar estimates reported in other settings—typically ranging from 0.3 to 0.7—for analysts (Bordalo, Gennaioli, La Porta, and Shleifer, 2019) and professional macroeconomic forecasters (Bordalo et al., 2020; L'Huillier et al., 2024). This negative association remains robust when fixed effects are gradually excluded (Columns 2-4) and when bank-level control variables are included (Column 5).[12]

Since the negative association remains robust after including bank fixed effects, this result is unlikely to be explained by certain banks being systematically more susceptible to regulatory pressure and consistently making overly pessimistic forecasts. In addition, as we will discuss in the analysis of MSA-level HPI forecasts (Section 5.5), the inclusion of bank × year-quarter fixed effects there alleviates concerns about regulatory pressure at the bank-year-quarter level, such as intensified scrutiny of weaker banks during crisis periods. To further mitigate this concern, we re-estimated our baseline regression separately on observations with positive and negative *NLCO_Rev*. As shown in Table OA3 in the Online Appendix, the negative association is only present in the subsample with positive *NLCO_Rev* (Columns 1 and 2). However, this is driven by the forecasts made after the onset of the pandemic. During the pre-pandemic period, the negative association is present and statistically significant for both subsamples, indicating that overreaction is present regardless of whether banks make optimistic or pessimistic forecast revisions (Columns 3 and 4). Hence, the negative association is unlikely to primarily reflect banks' overly pessimistic forecasts under regulatory pressure. After 2020, however, we observe the negative association only in the subsample of positive *NLCO_Rev* (Columns 5 and 6). This result is unlikely to stem from

[12] In our subsequent tests on the relation between forecast errors and forecast revisions, we follow prior research (e.g., Gennaioli et al., 2016; Bordalo et al., 2024c) by including bank fixed effects and year-quarter fixed effects. We do not include control variables to allow forecast revisions to capture signals in control variables that might be relevant for predicting future credit losses. Our results remain robust when control variables are included (untabulated).

regulatory pressure, because regulators do not have incentives to encourage overly pessimistic forecasts during downturns like the pandemic (see Section 2.3 for more institutional details). Instead, this finding likely reflects banks' overreaction to the adverse new information, consistent with the presence of the representativeness heuristic, as we discuss further in Section 5.5.

5.3 Horizon analysis for the representativeness heuristic in loan loss forecasts

To further explore the nature of overreaction in bank forecasts, we examine how the degree of overreaction changes across forecast horizons. We find that the negative association between forecast errors and forecast revisions becomes stronger for longer-horizon forecasts (Panel A of Table 3). This pattern remains robust when excluding all fixed effects (Panel B of Table 3) or when excluding only bank fixed effects or time fixed effects (Table OA4). This finding is consistent with an emerging set of studies that find overreaction in forecasts in other settings, such as equity analysts' earnings growth forecasts (Bordalo et al., 2024a), professional forecasters' interest rate expectations (Bordalo et al., 2020; d'Arienzo, 2020), and field data from betting and financial markets (Augenblick, Lazarus, and Thaler, 2023). The term structure of the extent of overreaction implies that the impact of the representativeness heuristic is more likely to manifest in longer-term NLCO forecasts. This pattern potentially contributes to the challenges in predicting cycle turns and long-term loan losses.

While the negative association in Table 3 generally intensifies from being small and insignificant at t+2 (i.e., a two-quarter horizon) to large and significant at t+5, the negative association at t+1 appears unexpectedly large and significant compared to that at t+2. A potential reason is that the significant negative association at t+1 arises from rapid mean reversion of forecast noise, whereas the negative associations beyond t+2 more plausibly reflect the representativeness heuristic. Specifically, since both the forecast error (actual minus current forecast) and forecast revision (current forecast minus previous forecast) depend on the same *current forecast*, noise in the current forecast can mechanically induce a negative association between the two measures. The noise and its mean reversion are more likely to contribute to the negative association for shorter-horizon forecasts, where the overreaction bias is less influential.

To distinguish between the mean reversion channel and the representativeness heuristic channel for the significant negative association at a one-quarter horizon, we conducted a cross-horizon test following Bordalo et al. (2020). Specifically, instead of regressing the forecast error at t+1 on the forecast revision at t+1, we now regress the forecast error at t+1 on the forecast revision at t+2 (both forecast errors and forecast revisions are still based on forecasts made at time t). In this test, since the "current forecast" used to calculate forecast error and forecast revision are different numbers, the noise in the current forecast for t+2, which only affects forecast revision, should not simultaneously affect the forecast error at t+1 (and vice versa). As a result, if the significant negative association at t+1 in Table 3 is primarily driven by the mean reversion of noise in forecasts, we should observe an insignificant association in the new test. In contrast, since the representativeness heuristic leads to systematic overreactions in forecasts, this bias should be positively correlated across forecast horizons (i.e., if a bank is overly optimistic about NLCO at t+1, it is likely to be overly optimistic about NLCO at t+2 as well). Therefore, we should still detect a significantly negative association between forecast error at t+1 and forecast revision at t+2 if the significant negative association at t+1 in Table 3 is due to overreaction.

In Panel A of Table 4, we find that forecast errors at t+1 are not significantly associated with forecast revisions at t+2 (Column 1). This suggests that the significant negative association at t+1 in Table 3 is likely driven by the mean reversion of noise in forecasts. We find the same result when regressing t+2 forecast error on t+3 forecast revision (Column 2). In contrast, forecast errors at horizons *t*+3, *t*+4, and *t*+5 are significantly negatively associated with forecast revisions at horizons *t*+4, *t*+5, and *t*+4, respectively (Columns 3 to 5).[13] These results provide further support for the presence of the representativeness heuristic in forecasts at horizons beyond two quarters. These results remain after excluding all fixed effects (Panel B of Table 4) or excluding only bank fixed effects or time fixed effects (Table OA5).

Our findings on the diminishing overreaction from long to short horizons suggest that this bias in forecasts resolves as time approaches the forecast target quarter. Under the representativeness heuristic, forecast revisions should be negatively correlated over a sufficiently long horizon, resolving the downward (upward) bias in forecasts over currently good (bad) conditions. If we view forecast errors as the final revision, our baseline result—a negative association between forecast revisions and forecast errors—represents a special case of a more general pattern of negatively correlated revisions over a sufficiently long horizon. To provide a more complete picture of this pattern and explore how overreaction resolves over time, we analyze the association between forecast revisions across multiple periods.

To empirically test the association between forecast revisions, we note that while banks typically issue forecasts at year-end, a subset made semi-annual forecasts during certain periods (see Section 2.3). These semi-annual forecasts are sporadic and cover only a subset of observations, but they allow us to calculate up to four distinct revisions for each target quarter.[14] We take advantage of these observations to investigate the association between revisions across multiple periods. As reported in Panel A of Table 5, each adjacent pair of revisions is negatively

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[13] Because the data does not allow us to calculate forecast revisions at horizon *t*+6, we regress *t*+5 forecast errors on *t*+4 forecast revisions.
[14] For instance, for the target quarter of 2020 Q1, a bank issuing semi-annual forecasts predicted the NLCO in 2020 Q1 for the first time in its nine-quarter-ahead forecast released in 2017 Q4. It then revised this forecast four times: in 2018 Q2, 2018 Q4, 2019 Q2, and finally 2019 Q4.

autocorrelated, with the absolute value of the autocorrelation coefficient less than one (Columns 2 to 4). In addition, the last revision (at a one-quarter horizon) is negatively associated with the corresponding forecast error, with the absolute value of the coefficient less than one (Column 1). The uniformly negative coefficients suggest that forecasts move toward realized NLCOs in a "jumpy" rather than smooth manner, consistent with banks overreacting to new information as it arrives. The absolute magnitude of each coefficient being less than one indicates that each revision overreacts to new information to a lesser extent than the previous one. Therefore, these results suggest that forecasts converge to realized NLCOs as overreaction attenuates with each revision. These results remain after excluding all fixed effects (Panel B of Table 5) or excluding only bank fixed effects or time fixed effects (Table OA6).

5.4 The influence of the representativeness heuristic on loan loss provision under CECL

Since overreaction affects banks' loan loss forecasts, a natural follow-up question is whether its impact is integrated into banks' loan loss provisions. Furthermore, given the greater overreaction in longer-term NLCO forecasts, as documented above, we expect overreaction to have a greater impact on the provisions of banks adopting CECL, which requires more forward-looking provisioning. We test this conjecture using a two-stage approach, following Bordalo et al. (2024b). In the first stage, we regress the NLCO forecast errors on NLCO forecast revisions.[15] The fitted values of NLCO forecast errors from this regression (*NLCO_Error_Fit*) capture the extent to which NLCO forecast errors can be explained by overreaction in forecast revisions. In the second stage, we use *NLCO_Error_Fit* as the independent variable to test whether it affects loan loss provisions (LLP), after controlling for bank characteristics related to credit risks.

[15] To be consistent, the first-stage regression includes all the fixed effects and control variables in the second stage.

As reported in Column 1 of Panel A of Table 6, *NLCO_Error_Fit* is negatively associated with LLP, indicating that overreaction in NLCO forecast affects LLP in the direction of overreaction (e.g., overestimated loan losses, captured by lower *NLCO_Error_Fit*, lead to higher LLP). In Column 2, we find that overreaction in NLCO forecasts has no effect on LLP for forecasts made in or before 2017, a pre-CECL period during which neither the forecast nor the realization is affected by CECL adoption in 2020.[16] This result is consistent with the notion that the overreaction bias primarily affects longer-term expectations, whereas provisioning under the incurred loss model (ILM) relies less on expected losses. To formally examine the effect of CECL adoption, we note that while all US banks in our sample adopted CECL in the first quarter of 2020, the US subsidiaries of foreign banks in our sample did not adopt CECL during the sample period. Therefore, we can construct an indicator variable, *CECLAdopter*, which takes the value of one for US banks starting in 2020 Q1, and regress provisions on the interaction between *NLCO_Error_Fit* and *CECLAdopter*.[17] We also include the interaction between *NLCO_Error_Fit* and the indicator for 2020 and later years to control for the pandemic's effect. As reported in Column 3, the effect of overreaction on LLP is particularly pronounced among CECL-adopting banks. These results suggest that overreaction leads to reduced (increased) provisions in good (bad) times, exacerbating the procyclicality of LLP, especially for CECL adopters. This is consistent with Chen et al.'s (2024) finding of increased procyclicality under CECL and suggests that overreaction in loan loss forecasts may be an underlying mechanism driving this effect.

[16] Since this regression uses predictions up to five quarters ahead, forecast errors of the five-quarter-ahead forecasts made in 2018 are affected by the realization in the first quarter of 2020. Hence, we use forecasts made in 2017 and earlier as a clean sample unaffected by the CECL adoption.
[17] Due to the COVID-19 pandemic, CECL adopters had the option to elect to use a CECL transition provision, which would delay the full impact of CECL on banks' regulatory capital. However, electing this option does not change the requirement that CECL adopters need to implement the new accounting standard for loan loss provisioning beginning in the first quarter of 2020. Since the focus of our analysis is the impact of CECL on banks' loan loss provision, we define CECL adoption based on whether a bank adopted CECL in the first quarter of 2020.

If overreaction has a greater impact after CECL adoption because CECL-adopting banks incorporate longer-horizon forecasts, we should expect the magnitude of the coefficient of *NLCO_Error_Fit*CECLAdopter* to increase for longer-horizon forecasts. In Panel B of Table 6, we re-run the same regression as in Panel A for each forecast horizon and find supporting evidence: the magnitude of the coefficient of *NLCO_Error_Fit*CECLAdopter* for longer horizon forecasts (Columns 3-5) is larger than that for shorter horizon forecasts (Columns 1 and 2).

Recent research by Granja and Nagel (2025) finds that CECL has a greater effect in increasing the interest rates of longer-maturity loans due to the incremental provisioning for longer-term expected defaults under the new standard. We extend this insight and examine how the effect of CECL on the sensitivity of LLP to overreaction in forecasts varies with loan maturity. We use the percentage of loans that reprice or mature within one year, *FloatLoanRatio*, as an inverse proxy for loan maturity. Next, we construct an indicator of longer loan maturity, *LoanMaturity_High*, which takes the value of one if *FloatLoanRatio* is below the median. In Table 6, Panel C, Column 1, we first document that, generally, the LLP of banks holding longer-maturity loans is not more sensitive to overreaction than that of banks holding shorter-maturity loans. When we focus on CECL adopters in Column 2, however, we find that the coefficient of the three-way interaction between *NLCO_Error_Fit*, *CECLAdopter*, and *LoanMaturity_High* is significantly negative, indicating that the impact of overreaction on LLP under CECL is stronger for banks holding longer-maturity loans. This is likely because forecasts for longer-maturity loans are more susceptible to overreaction, making LLP under CECL more sensitive to this bias for banks holding longer-maturity loans. Our results imply that the representativeness heuristic contributes to CECL's greater impact on banks with portfolios of longer-maturity loans.

5.5 Robustness and prevalence of representativeness heuristic in bank forecasts

We conduct a series of additional tests exploiting more granular data to investigate the robustness and prevalence of overreaction in bank forecasts. First, we examine the NLCO forecasts separately for real estate loans, C&I loans, and consumer loans. Table 7 reports results consistent with the baseline: overreaction is present in the loan loss forecasts for all three loan types. These results remain after excluding all fixed effects or excluding only bank fixed effects or time fixed effects (Table OA7).

Second, we examine the impact of the COVID-19 pandemic, a major macroeconomic shock during our sample period. This test not only allows us to examine the role of macroeconomic forces in shaping bank forecasts but also helps alleviate concerns about an alternative explanation for our findings. Specifically, our results could simply be explained by the unexpected COVID-19 relief that reduced banks' loan losses in 2020 Q2 and beyond, leading to negatively associated forecast revisions and errors for forecasts made immediately *before* 2020 (for target quarters after the onset of the pandemic). In contrast, the theory underlying the representativeness heuristic predicts a stronger negative correlation in forecasts made *after* the shock, i.e., *in* 2020, because forecasts influenced by the bias tend to overreact to major shocks like the onset of the pandemic in early 2020 (Bordalo et al., 2018; Fahlenbrach et al., 2018).[18]

Table 8 reports the results of this analysis. Column 1 documents the presence of overreaction in forecasts made in or before 2017, a clean sample period during which neither the forecasts nor the realization of the predicted numbers were affected by the COVID-19 shock. This result suggests that overreaction in bank forecasts exists independently of the influence of the pandemic. Moreover, Columns 2 and 3 suggest that forecasts made in 2018 and 2019 do not exhibit

[18] Since forecasts in our sample are primarily made at year-end (with some made at mid-year), the 2020 forecasts are made after the onset of the pandemic.

a stronger negative correlation between forecast errors and revisions; if anything, the correlation appears weaker, especially for the 2019 forecasts. These findings contradict the predictions of the alternative explanation. In contrast, in Column 4, we detect a significantly stronger negative correlation between forecast revisions and forecast errors for forecasts made in 2020, consistent with banks overreacting to the macroeconomic shock at the onset of the pandemic. These results remain after excluding all fixed effects or excluding only bank fixed effects or time fixed effects (Table OA8). Overall, our findings support the theoretical prediction that macroeconomic shocks intensify overreaction in forecasts and mitigate the concerns of the alternative explanation.

Third, we examine whether banks' macroeconomic forecasts, a key input for their loan loss forecasts, demonstrate overreaction. In this analysis, we focus on banks' forecasts of the MSA-level house price index (HPI). Leveraging our granular data at the bank-year-quarter-MSA level, we incorporate MSA-year-quarter fixed effects to control for the influence of common local shocks. In addition, we include bank-year-quarter fixed effects to control for time-varying, bank-specific factors, alleviating concerns that our results can be driven by regulatory pressure and other forces at the bank-year-quarter level, such as intensified scrutiny of weaker banks during crisis periods. Table 9 documents a significant negative correlation between HPI forecast revisions and forecast errors, providing further evidence of overreaction in bank forecasts. Moreover, consistent with our findings in Table 5, this overreaction is more pronounced at longer forecast horizons (four quarters ahead, Column 3) compared to shorter ones (two quarters ahead, Column 2). We also find overreaction in HPI forecasts during the pre-COVID period (Column 4).[19]

[19] Since this regression uses predictions two and four quarters ahead, forecast errors of the four-quarter-ahead forecasts made in 2018 are affected by the realization in the fourth quarter of 2019, before the onset of the pandemic. Hence, we use forecasts made in 2018 and earlier as a clean sample unaffected by the pandemic.

Finally, the MSA-level data allows us to investigate whether banks are more likely to overreact in regions where they have a stronger operating presence. Recent research suggests that forecasters tend to overreact more when forming expectations about assets they own, likely because they pay closer attention to information related to their holdings (Hartzmark et al., 2021). We test whether banks exhibit greater overreaction in MSAs where they have the largest number of branches. Consistent with this pattern, in Table 10, we find that the extent of overreaction is 22% (-0.0727/-0.3292), 23% (-0.0763/-0.3297), and 28% (-0.0916/-0.3303) greater in MSAs where banks have branch presence in the top 10, top 5, and top 1 percentiles, respectively, compared to other MSAs.

6. Conclusion

Loan loss forecasts are central to banks' loan loss recognition. In this study, we leverage confidential supervisory data to provide evidence that banks' loan loss forecasts systematically deviate from rational expectations in a manner consistent with being influenced by the representativeness heuristic. Specifically, we find that revisions in net loan charge-off (NLCO) forecasts (current forecast minus previous forecast) are negatively associated with the corresponding forecast errors (actual minus current forecast). This pattern reflects overreaction in forecasts as predicted by the representativeness heuristic, and it is more pronounced for longer-horizon forecasts. Successive forecast revisions targeting the same future NLCO are negatively autocorrelated, with the absolute value of the autocorrelation coefficients less than one, indicating a gradual resolution of overreaction over time. Overreaction in NLCO forecasts also affects loan loss provisions (LLP) in the same direction as the forecast bias, especially for banks that have adopted CECL. The impact of overreaction on CECL-adopting banks' LLP intensifies for longer-horizon forecasts and for banks with longer-maturity loans. Moreover, the overreaction is present in loan loss forecasts across loan types and extends to predictions of regional macroeconomic conditions.

Our paper provides novel insights into the factors influencing loan loss recognition and the effect of CECL. Our findings support the view that limited forecasting ability may contribute to banks' increased procyclicality, especially under CECL (Ryan, 2019; Chen et al., 2025; Vidinova, 2024). By focusing on a behavioral factor, we respond to Hanlon et al.'s (2022) call to incorporate the "people dimension" into the explanations of accounting phenomena. Our paper also provides empirical evidence of systematic errors in bank forecasts that underpin the explanations of credit cycles and financial crises in the behavioral finance literature (Barron and Xiong, 2017; Bordalo et al., 2018; Fahlenbrach et al, 2018).

The findings in this paper should be interpreted with at least two caveats in mind. First, the internal forecasts analyzed are derived from reports submitted to bank regulators and are not publicly disclosed. Therefore, factors that influence these forecasts (e.g., those in the FR Y-14A filings) may differ from those underlying publicly disclosed forecasts, such as management guidance. While this feature allows us to observe forecasts less affected by market pressure, our findings might not be directly applicable in other reporting settings where forward-looking information is publicly disclosed. Second, our sample is limited to the largest banks in the United States and may not be generalizable to all banks. Nonetheless, because these banks account for a significant share of total banking assets, understanding their forecast behavior is crucial for bank regulation and policymaking.

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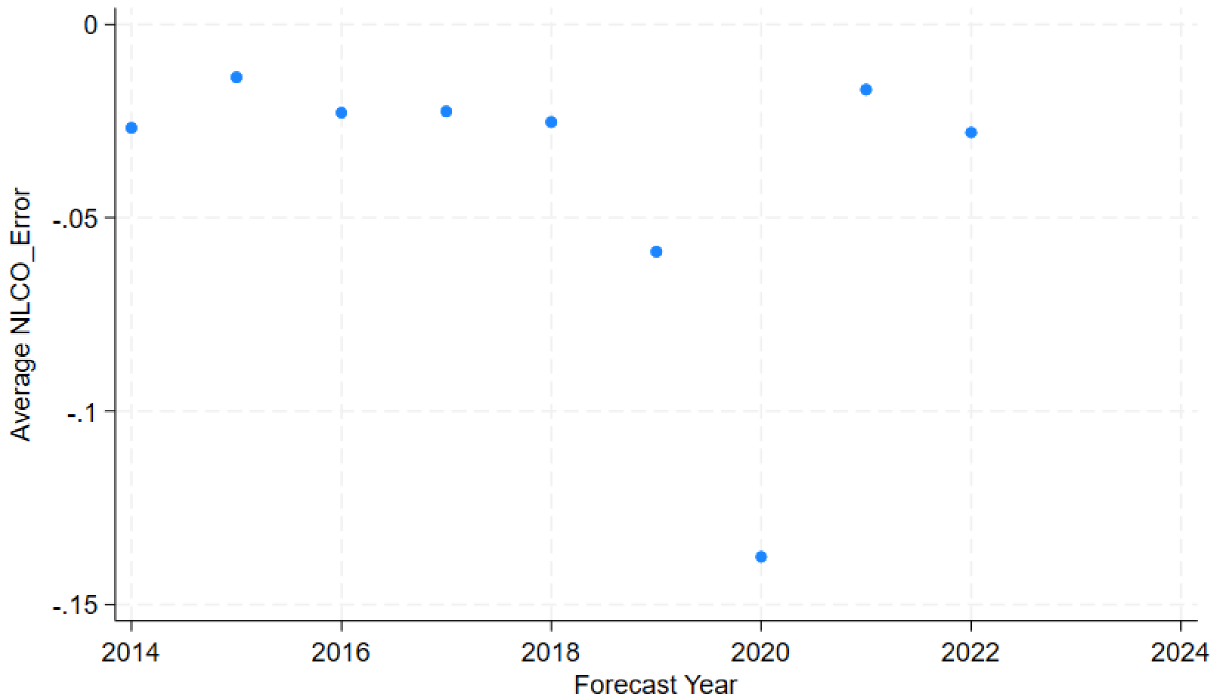
Appendix A. Variable Definition

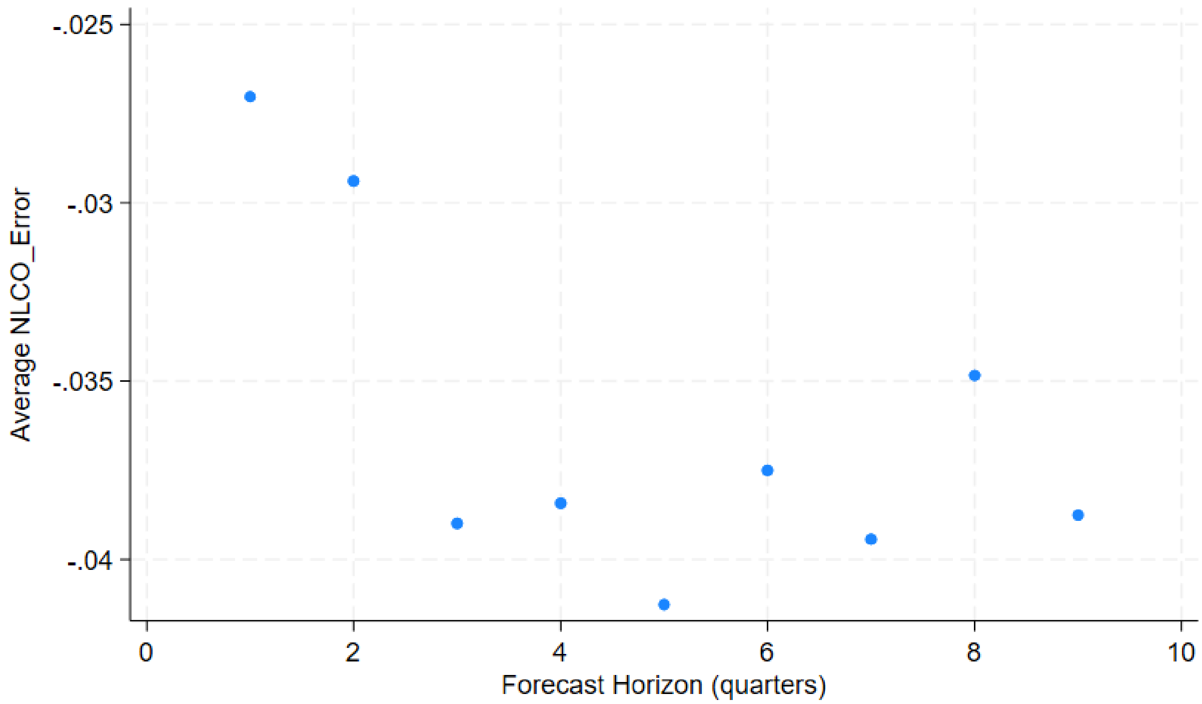
Variable	Variable Definition
CapR	The ratio of equity to assets × 100. The variable is measured in the quarter in which the forecasts are issued.
CECLAdopter	An indicator variable equal to one if the bank has adopted CECL in the forecasting quarter according to call report disclosure, and zero otherwise. The variable is measured in the quarter in which the forecasts are issued.
Cons	The proportion of consumer loans × 100. The variable is measured in the quarter in which the forecasts are issued.
FloatLoanRatio	The percentage of loans that reprice or mature within one year × 100. The variable is measured in the quarter in which the forecasts are issued.
HPI_Error	Actual future house price index (HPI) minus predicted HPI corresponding to the actual number.
HPI_Rev	The most recent forecast for a certain quarter's HPI minus a forecast made a year before the latest forecast for the same quarter's HPI.
LLP	The annualized loan loss provisions (i.e., the sum of provisions in the forecast quarter and the previous three quarters) scaled by average loans outstanding × 100.
Loansyield	The tax-equivalent interest rate on loans × 100. The variable is measured in the quarter in which the forecasts are issued.
NLCO	The ratio of net loan charge-offs to average loans outstanding × 100. The variable is measured in the quarter in which the forecasts are issued.
NLCO_Error	Actual future *NLCO* minus predicted *NLCO* corresponding to the actual number. The variable is constructed over nine separate horizons and then pooled.
NLCO_Rev	The most recent forecast for a certain quarter's *NLCO* minus a forecast made a year before the latest forecast for the same quarter's *NLCO*. The variable is constructed over five separate horizons and then pooled.
$NLCO\_Rev\_SA_{t\|t-h}$	The forecast made in quarter t-h for the *NLCO* in quarter t minus the forecast made in quarter t-h-2 for the same *NLCO* in quarter t. h=1, 3, 5, or 7.
NLCO_CNI_Error	Forecast error (defined in the same way as *NLCO_Error*) of commercial and industrial loan losses. The variable is constructed over nine separate horizons and then pooled.
NLCO_ CNI _Rev	Forecast revision (defined in the same way as *NLCO_Rev*) of commercial and industrial loan losses. The variable is constructed over five separate horizons and then pooled.
NLCO_CO_Error	Forecast error (defined in the same way as *NLCO_Error*) of consumer loan losses. The variable is constructed over nine separate horizons and then pooled.
NLCO_CO_Rev	Forecast revision (defined in the same way as *NLCO_Rev*) of consumer loan losses. The variable is constructed over five separate horizons and then pooled.
NLCO_RE_Error	Forecast error (defined in the same way as *NLCO_Error*) of real estate loan losses. The variable is constructed over nine separate horizons and then pooled.
NLCO_RE_Rev	Forecast revision (defined in the same way as *NLCO_Rev*) of real estate loan losses. The variable is constructed over five separate horizons and then pooled.
Real	The proportion of real estate loans × 100. The variable is measured in the quarter in which the forecasts are issued.
Size	The natural logarithm of total assets × 100. The variable is measured in the quarter in which the forecasts are issued.

Figure 1. Average net loan charge-off forecast errors by forecast year



Notes: This figure reports *NLCO_Error*, averaged across banks and forecast horizons, for each of the forecast years. *NLCO_Error* is the forecast error of the *NLCO* prediction. *NLCO* is the ratio of net loan charge-offs to average loans outstanding.

Figure 2. Average net loan charge-off forecast errors by forecast horizon



Notes: This figure reports the average *NLCO_Error* for each of the nine forecast horizons. *NLCO_Error* is the forecast error of the *NLCO* prediction. *NLCO* is the ratio of net loan charge-offs to average loans outstanding.

Table 1. Summary statistics

	N	Mean	Std. Dev.	Q1	Median	Q3
NLCO	2,069	0.1359	0.1894	0.0426	0.0762	0.1292
NLCO_Error	2,069	-0.0362	0.0769	-0.0478	-0.0183	-0.0029
NLCO_Rev	787	0.0092	0.0642	-0.0110	-0.0020	0.0149
NLCO_Rev_SA$_{t\|t-1}$	135	-0.0051	0.0730	-0.0145	0.0003	0.0085
NLCO_Rev_SA$_{t\|t-3}$	138	0.0025	0.0739	-0.0093	-0.0012	0.0072
NLCO_Rev_SA$_{t\|t-5}$	138	0.0103	0.0633	-0.0091	-0.0011	0.0063
NLCO_Rev_SA$_{t\|t-7}$	138	0.0053	0.0530	-0.0098	-0.0012	0.0062
LLP	2,781	0.5980	0.9588	0.1496	0.2907	0.5671
Size (raw; $bn)	2,799	800.1	916.3	139.4	373.6	1,188.1
CapR	2,799	11.2344	1.7952	9.8285	11.1361	12.4832
Loansyield	2,799	4.6652	1.8998	3.5852	4.1389	4.9021
FloatLoanRatio	2,799	49.3797	7.6747	44.0588	49.0450	52.6886
Real	2,799	37.5628	12.1466	29.6184	37.4907	43.3035
Cons	2,799	17.3405	14.1463	8.2288	14.3566	21.5157
CECLadopter	2,799	0.1897	0.3921	0.0000	0.0000	0.0000
NLCO_RE_Error	2,069	-0.0379	0.0437	-0.0570	-0.0294	-0.0130
NLCO_RE_Rev	787	0.0047	0.0400	-0.0127	-0.0020	0.0105
NLCO_CNI_Error	2,069	-0.0270	0.0960	-0.0635	-0.0255	0.0109
NLCO_CNI_Rev	787	0.0162	0.0846	-0.0221	-0.0022	0.0330
NLCO_CO_Error	2,069	-0.0440	0.2325	-0.0689	-0.0025	0.0322
NLCO_CO_Rev	787	0.0400	0.1714	-0.0112	0.0130	0.0522
HPI_Error	52,023	0.0491	0.0856	-0.0007	0.0294	0.0797
HPI_Rev	33,266	0.0516	0.1184	-0.0100	0.0281	0.0779

Notes: This table reports summary statistics for key variables in regressions. We winsorize all continuous variables at the top and bottom one percent to mitigate the influence of extreme values. Q1 and Q3 refer to the 25th percentile and 75th percentile, respectively. The definitions of the variables reported in the table are available in Appendix A.

Table 2. Representativeness heuristic in loan loss forecast

	(1) *NLCO_Error*	(2) *NLCO_Error*	(3) *NLCO_Error*	(4) *NLCO_Error*	(5) *NLCO_Error*
NLCO_Rev	-0.5372***	-0.5503***	-0.6444***	-0.6693***	-0.5503***
	(-3.19)	(-3.15)	(-3.53)	(-3.74)	(-5.15)
Observations	775	775	775	775	775
Adjusted R-squared	0.598	0.460	0.445	0.308	0.659
Bank Fixed Effects	Yes	No	Yes	No	Yes
Year-quarter Fixed Effects	Yes	Yes	No	No	Yes
Horizon Fixed Effect	Yes	Yes	Yes	No	Yes
Controls	No	No	No	No	Yes

Notes: This table reports estimates from the OLS regressions of loan loss forecast errors on loan loss forecast revisions. *NLCO_Error* is the forecast error of the *NLCO* prediction. *NLCO_Rev* is the forecast revision of the *NLCO* prediction. *Controls* include *Size*, *CapR*, *NLCO*, *Loansyield*, *FloatLoanRatio*, *Real*, and *Cons*, as defined in Appendix A. All control variables are measured in the quarter in which the forecasts are issued. The dependent variable is constructed over five separate horizons and then pooled. Robust *t*-statistics in parentheses are based on standard errors clustered at the bank level. ***, **, * indicate statistical significance at less than 1, 5, and 10%, respectively.

Table 3. Representativeness heuristic in loan loss forecast by forecast horizon

Panel A. Main specification

	(1) *NLCO_Error* (*h*=1)	(2) *NLCO_Error* (*h*=2)	(3) *NLCO_Error* (*h*=3)	(4) *NLCO_Error* (*h*=4)	(5) *NLCO_Error* (*h*=5)
NLCO_Rev	-0.3764**	-0.1282	-0.4868*	-0.4121*	-0.5360**
	(-2.13)	(-0.47)	(-2.00)	(-1.85)	(-2.38)
Observations	154	154	154	154	154
Adjusted R-squared	0.580	0.427	0.683	0.608	0.694
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year-quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes

Panel B. Without fixed effects

	(1) *NLCO_Error* (*h*=1)	(2) *NLCO_Error* (*h*=2)	(3) *NLCO_Error* (*h*=3)	(4) *NLCO_Error* (*h*=4)	(5) *NLCO_Error* (*h*=5)
NLCO_Rev	-0.4017**	-0.2585	-0.7624**	-0.7817***	-0.9482***
	(-2.23)	(-0.82)	(-2.67)	(-5.40)	(-8.24)
Observations	155	155	155	155	155
Adjusted R-squared	0.239	0.072	0.344	0.324	0.484
Bank Fixed Effects	No	No	No	No	No
Year-quarter Fixed Effects	No	No	No	No	No

Notes: This table reports estimates from the OLS regressions of loan loss forecast errors on loan loss forecast revisions for each forecast horizon, ranging from one quarter ahead (*h*=1) to five quarters ahead (*h*=5). *NLCO_Error* is the forecast error of the *NLCO* prediction. *NLCO_Rev* is the forecast revision of the *NLCO* prediction. Robust *t*-statistics in parentheses are based on standard errors clustered at the bank level. ***, **, * indicate statistical significance at less than 1, 5, and 10%, respectively.

Table 4. Mean reversion of noise in forecasts vs. representativeness heuristic

Panel A. Main specification

VARIABLES	(1) *NLCO_Error* (*h*=1)	(2) *NLCO_Error* (*h*=2)	(3) *NLCO_Error* (*h*=3)	(4) *NLCO_Error* (*h*=4)	(5) *NLCO_Error* (*h*=5)
NLCO_Rev (*h*=2)	-0.0158				
	(-0.11)				
NLCO_Rev (*h*=3)		-0.1717			
		(-0.76)			
NLCO_Rev (*h*=4)			-0.5137***		-0.3710*
			(-3.18)		(-1.90)
NLCO_Rev (*h*=5)				-0.4695***	
				(-2.89)	
Observations	154	154	154	154	154
Adjusted R-squared	0.460	0.444	0.678	0.617	0.654
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year-quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes

Panel B. Without fixed effects

VARIABLES	(1) *NLCO_Error* (*h*=1)	(2) *NLCO_Error* (*h*=2)	(3) *NLCO_Error* (*h*=3)	(4) *NLCO_Error* (*h*=4)	(5) *NLCO_Error* (*h*=5)
NLCO_Rev (*h*=2)	-0.1891				
	(-1.07)				
NLCO_Rev (*h*=3)		-0.3563			
		(-1.55)			
NLCO_Rev (*h*=4)			-0.8527***		-0.8200***
			(-4.70)		(-5.06)
NLCO_Rev (*h*=5)				-0.7983***	
				(-8.96)	
Observations	155	155	155	155	155
Adjusted R-squared	0.057	0.177	0.413	0.361	0.337
Bank Fixed Effects	No	No	No	No	No
Year-quarter Fixed Effects	No	No	No	No	No

Notes: This table reports estimates from the OLS regressions of loan loss forecast errors at a given horizon on loan loss forecast revisions at a different horizon (e.g., regressing forecast errors at one-quarter horizon, i.e., *h*=1, on forecast revisions at two-quarter horizon, i.e., *h*=2, as reported in column 1). *NLCO_Error* is the forecast error of the *NLCO* prediction. *NLCO_Rev* is the forecast revision of the *NLCO* prediction. Robust *t*-statistics in parentheses are based on standard errors clustered at the bank level. ***, **, * indicate statistical significance at less than 1, 5, and 10%, respectively.

Table 5. Associations among forecast revisions over time

Panel A. Main specification

	(1) $NLCO\_Error_{t\|t-1}$	(2) $NLCO\_Rev\_SA_{t\|t-1}$	(3) $NLCO\_Rev\_SA_{t\|t-3}$	(4) $NLCO\_Rev\_SA_{t\|t-5}$
$NLCO\_Rev\_SA_{t\|t-1}$	-0.1707**			
	(-2.55)			
$NLCO\_Rev\_SA_{t\|t-3}$		-0.6668**		
		(-2.76)		
$NLCO\_Rev\_SA_{t\|t-5}$			-0.4212*	
			(-1.90)	
$NLCO\_Rev\_SA_{t\|t-7}$				-0.3452**
				(-2.30)
Observations	134	114	116	116
Adjusted R-squared	0.497	0.709	0.380	0.563
Bank Fixed Effects	Yes	Yes	Yes	Yes
Year-quarter Fixed Effects	Yes	Yes	Yes	Yes

Panel B. Without fixed effects

	(1) $NLCO\_Error_{t\|t-1}$	(2) $NLCO\_Rev\_SA_{t\|t-1}$	(3) $NLCO\_Rev\_SA_{t\|t-3}$	(4) $NLCO\_Rev\_SA_{t\|t-5}$
$NLCO\_Rev\_SA_{t\|t-1}$	-0.1411			
	(-1.61)			
$NLCO\_Rev\_SA_{t\|t-3}$		-0.8242***		
		(-4.35)		
$NLCO\_Rev\_SA_{t\|t-5}$			-0.5435***	
			(-4.02)	
$NLCO\_Rev\_SA_{t\|t-7}$				-0.3955**
				(-2.55)
Observations	135	115	117	117
Adjusted R-squared	0.039	0.537	0.169	0.094
Bank Fixed Effects	No	No	No	No
Year-quarter Fixed Effects	No	No	No	No

Notes: This table reports estimates from the OLS regressions of semi-annual NLCO forecast revision, *NLCO_Rev_SA*, estimated in quarter *t*-1, *t*-3, and *t*-5 on the same variable estimated in quarter *t*-3, *t*-5, and *t*-7, respectively. $NLCO\_Rev\_SA_{t|t-h}$ is the forecast made in quarter *t-h* for the *NLCO* in quarter *t* minus the forecast made in quarter *t*-*h*-2 for the same *NLCO* in quarter *t*. $NLCO\_Error_{t|t-1}$ is *NLCO* in quarter *t* minus the forecast made in quarter *t*-1 for the same *NLCO* in quarter *t*. Robust *t*-statistics in parentheses are based on standard errors clustered at the bank level. ***, **, * indicate statistical significance at less than 1, 5, and 10%, respectively.

Table 6. The influence of the representativeness heuristic on loan loss provision

Panel A. Full sample

	(1) *LLP*	(2) *LLP* Year ≤ 2017	(3) *LLP*
NLCO_Error_Fit	-1.3550**	-0.0678	-0.6862
	(-2.30)	(-0.18)	(-0.85)
*NLCO_Error_Fit*CECLAdopter*			-2.0885**
			(-2.38)
*NLCO_Error_Fit*Post2020*			1.0670
			(1.22)
CECLAdopter			-0.0718
			(-0.46)
Observations	775	305	775
Adjusted R-squared	0.917	0.982	0.922
Controls	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes
Year-quarter Fixed Effects	Yes	Yes	Yes
Horizon Fixed Effect	Yes	Yes	Yes

Notes: This table reports estimates from two-stage least squares (2SLS) regressions. The first stage estimates loan loss forecast errors that are predicted by forecast revisions (untabulated). The second stage estimates loan loss provisions as a function of the fitted forecast errors, *NLCO_Error_Fit*. *LLP* is the annualized loan loss provisions (i.e., the sum of provisions in the forecast quarter and the previous three quarters) scaled by average loans outstanding. *CECLAdopter* is an indicator variable equal to one if the bank has adopted CECL in the forecasting quarter according to call report disclosure, and zero otherwise. *Post2020* is an indicator equal to one for forecasts made in and after 2020 and zero otherwise. *Controls* include *Size*, *CapR*, *NLCO*, *Loansyield*, *FloatLoanRatio*, *Real*, and *Cons*, as defined in Appendix A. Robust *t*-statistics in parentheses are based on standard errors clustered at the bank level. ***, **, * indicate statistical significance at less than 1, 5, and 10%, respectively.

Panel B. The influence of the representativeness heuristic on CECL adopters, by forecast horizon

	(1) *LLP* (*h*=1)	(2) *LLP* (*h*=2)	(3) *LLP* (*h*=3)	(4) *LLP* (*h*=4)	(5) *LLP* (*h*=5)
NLCO_Error_Fit	-0.0978	0.7032	-1.0421	-2.5579***	-3.0989*
	(-0.05)	(0.35)	(-0.76)	(-3.61)	(-1.74)
*NLCO_Error_Fit*CECLAdopter*	-1.8229**	-1.6384*	-2.6265***	-2.2931**	-2.3378**
	(-2.11)	(-1.77)	(-3.20)	(-2.23)	(-2.34)
*NLCO_Error_Fit*Post2020*	0.8064	0.6917	1.5349*	1.3124	1.5863
	(0.82)	(0.59)	(1.82)	(1.26)	(1.63)
CECLAdopter	-0.0031	-0.0191	-0.1298	-0.1341	-0.1293
	(-0.02)	(-0.14)	(-0.74)	(-0.78)	(-0.71)
Observations	154	154	154	154	154
Adjusted R-squared	0.898	0.897	0.902	0.909	0.911
Controls	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year-quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes

Notes: This table reports estimates from two-stage least squares (2SLS) regressions. The first stage estimates loan loss forecast errors that are predicted by forecast revisions (untabulated). The second stage estimates loan loss provisions as a function of the interaction between the fitted forecast errors, *NLCO_Error_Fit*, and the indicator *CECLAdopter*, for each forecast horizon, ranging from one quarter ahead (*h*=1) to five quarters ahead (*h*=5). *LLP* is the annualized loan loss provisions (i.e., the sum of provisions in the forecast quarter and the previous three quarters) scaled by average loans outstanding. *CECLAdopter* is an indicator variable equal to one if the bank has adopted CECL in the forecasting quarter according to call report disclosure, and zero otherwise. *Post2020* is an indicator equal to one for forecasts made in and after 2020 and zero otherwise. *Controls* include *Size*, *CapR*, *NLCO*, *Loansyield*, *FloatLoanRatio*, *Real*, and *Cons*, as defined in Appendix A. Robust *t*-statistics in parentheses are based on standard errors clustered at the bank level. ***, **, * indicate statistical significance at less than 1, 5, and 10%, respectively.

Panel C. The influence of the representativeness heuristic on CECL adopters with longer maturity loans

	(1) LLP	(2) LLP
*NLCO_Error_Fit*CECLAdopter*LoanMaturity_High*		-2.4506*
		(-2.09)
*CECLAdopter*LoanMaturity_High*		0.0087
		(0.08)
*NLCO_Error_Fit*CECLAdopter*		-0.2595
		(-0.46)
*NLCO_Error_Fit*LoanMaturity_High*	-0.0759	1.0306**
	(-0.16)	(2.29)
LoanMaturity_High	0.2014*	0.1167
	(1.74)	(1.05)
NLCO_Error_Fit	-1.3240*	-0.7098
	(-2.07)	(-0.96)
CECLAdopter		-0.1443
		(-1.19)
Observations	775	775
Adjusted R-squared	0.922	0.938
Controls	Yes	Yes
Bank Fixed Effects	Yes	Yes
Year-quarter Fixed Effects	Yes	Yes
Horizon Fixed Effect	Yes	Yes

Notes: This table reports estimates from two-stage least squares (2SLS) regressions. The first stage estimates loan loss forecast errors that are predicted by forecast revisions (untabulated). The second stage estimates loan loss provisions as a function of the interaction between the fitted forecast errors, *NLCO_Error_Fit*, and indicator variables *CECLAdopter* and *LoanMaturity_High*. *LLP* is the annualized loan loss provisions (i.e., the sum of provisions in the forecast quarter and the previous three quarters) scaled by average loans outstanding. *CECLAdopter* is an indicator variable equal to one if the bank has adopted CECL in the forecasting quarter according to call report disclosure, and zero otherwise. *LoanMaturity_High* is an indicator variable equal to one if *FloatLoanRatio* is below the median, and zero otherwise. *FloatLoanRatio* is the percentage of loans that reprice or mature within one year. *Post2020* is an indicator equal to one for forecasts made in and after 2020 and zero otherwise. *Controls* include *Size*, *CapR*, *NLCO*, *Loansyield*, *FloatLoanRatio*, *Real*, and *Cons*, as defined in Appendix A. Robust *t*-statistics in parentheses are based on standard errors clustered at the bank level. ***, **, * indicate statistical significance at less than 1, 5, and 10%, respectively.

Table 7. Representativeness heuristic in loan loss forecast for different loan types

	(1) *NLCO_RE_Error*	(2) *NLCO_CNI_Error*	(3) *NLCO_CO_Error*
NLCO_RE_Rev	-0.7398***		
	(-14.19)		
NLCO_CNI_Rev		-0.5657***	
		(-4.65)	
NLCO_CO_Rev			-0.6169***
			(-6.82)
Observations	775	775	775
Adjusted R-squared	0.785	0.483	0.508
Bank Fixed Effects	Yes	Yes	Yes
Year-quarter Fixed Effects	Yes	Yes	Yes
Horizon Fixed Effect	Yes	Yes	Yes

Notes: This table reports estimates from the OLS regressions of loan loss forecast errors on their corresponding forecast revisions for different loan types. *NLCO_RE_Error*, *NLCO_CNI_Error*, and *NLCO_CO_Error* (*NLCO_RE_Rev*, *NLCO_CNI_Rev*, and *NLCO_CO_Rev*) are forecast errors (revisions) of loan losses for real estate loans, commercial and industrial loans, and consumer loans, respectively. Forecast error and forecast revision of all loan types are defined in the same way as *NLCO_Error* and *NLCO_Rev*. Robust *t*-statistics in parentheses are based on standard errors clustered at the bank level. ***, **, * indicate statistical significance at less than 1, 5, and 10%, respectively.

Table 8. Representativeness heuristic in loan loss forecast during the COVID-19 pandemic

	(1) *NLCO_Error* Year ≤ 2017	(2) *NLCO_Error*	(3) *NLCO_Error*	(4) *NLCO_Error*
NLCO_Rev	-0.6480***	-0.5427***	-0.5686***	-0.2753
	(-19.30)	(-3.02)	(-3.53)	(-1.51)
*NLCO_Rev*Year2018*		0.0983		
		(0.43)		
*NLCO_Rev*Year2019*			0.7347***	
			(8.80)	
*NLCO_Rev*Year2020*				-0.5333***
				(-4.07)
Observations	305	775	775	775
Adjusted R-squared	0.556	0.598	0.608	0.634
Bank Fixed Effects	Yes	Yes	Yes	Yes
Year-quarter Fixed Effects	Yes	Yes	Yes	Yes
Horizon Fixed Effect	Yes	Yes	Yes	Yes

Notes: This table reports estimates from the OLS regressions of loan loss forecast errors on loan loss forecast revisions. Column 1 only includes forecasts made during 2014-2017. Column 2 (3, 4) uses the full sample and includes the interaction between forecast revision and an indicator of 2018 (2019, 2020). *NLCO_Error* is the forecast error of the *NLCO* prediction. *NLCO_Rev* is the forecast revision of the *NLCO* prediction. Robust *t*-statistics in parentheses are based on standard errors clustered at the bank level. ***, **, * indicate statistical significance at less than 1, 5, and 10%, respectively.

Table 9. Representativeness heuristic in house price index (HPI) forecast

	(1) *HPI_Error*	(2) *HPI_Error* *h*=2	(3) *HPI_Error* *h*=4	(4) *HPI_Error* Year ≤ 2018
HPI_Rev	-0.3306*** (-4.38)	-0.1662*** (-10.86)	-0.4280*** (-6.69)	-0.1897*** (-7.57)
Observations	20,388	9,035	11,351	4,527
Adjusted R-squared	0.735	0.407	0.789	0.297
Bank-Year-Quarter Fixed Effects	Yes	Yes	Yes	Yes
MSA-Year-Quarter Fixed Effects	Yes	Yes	Yes	Yes
Horizon Fixed Effect	Yes	No	No	Yes

Notes: This table reports estimates from the OLS regressions of MSA-level HPI forecast errors on MSA-level HPI forecast revisions for the full sample, forecasts with a two-quarter horizon (*h*=2), forecasts with a four-quarter horizon (*h*=4), and forecasts made in and before 2018 only. *HPI_Error* is the forecast error of the *HPI* prediction. *HPI_Rev* is the forecast revision of the *HPI* prediction. Robust *t*-statistics in parentheses are based on standard errors clustered at the bank level. ***, **, * indicate statistical significance at less than 1, 5, and 10%, respectively.

Table 10. Representativeness heuristic in house price index (HPI) forecast conditional on branch exposure

	(1) *HPI_Error*	(2) *HPI_Error*	(3) *HPI_Error*
HPI_Rev	-0.3292***	-0.3297***	-0.3303***
	(-4.39)	(-4.39)	(-4.39)
*HPIREV*BranchTop10%*	-0.0727		
	(-1.61)		
BranchTop10%	0.0063		
	(1.06)		
*HPIREV*BranchTop5%*		-0.0763**	
		(-2.65)	
BranchTop5%		0.0002	
		(0.07)	
*HPIREV*BranchTop1%*			-0.0916*
			(-2.10)
BranchTop1%			0.0014
			(0.46)
Observations	20,388	20,388	20,388
Adjusted R-squared	0.735	0.735	0.735
Bank-Year-Quarter Fixed Effects	Yes	Yes	Yes
MSA-Year-Quarter Fixed Effects	Yes	Yes	Yes
Horizon Fixed Effect	Yes	Yes	Yes

Notes: This table reports estimates from the OLS regressions of HPI forecast errors on the interactions between HPI forecast revisions and indicators of branch exposure in an MSA. *HPI_Error* is the forecast error of the *HPI* prediction. *HPI_Rev* is the forecast revision of the *HPI* prediction. *BranchTop10%* (*BranchTop5%*, *BranchTop1%*) is an indicator variable equal to one if the number of branches in an MSA falls within the top 10 (5, 1) percentile among all MSAs where the bank has a branch exposure. Robust *t*-statistics in parentheses are based on standard errors clustered at the bank level. ***, **, * indicate statistical significance at less than 1, 5, and 10%, respectively.

Online Appendix for "Imperfect Expectations in Loan Loss Forecast"

Table OA1. Forecast revision and bank decisions

	(1) *LLP*	(2) *LLP*
NLCO_Rev	0.7456**	1.1814**
	(2.30)	(2.62)
Tier1Cap_Rev		0.0537*
		(1.78)
ROA_Rev		0.0980
		(0.49)
CoreRate_Rev		0.0067
		(0.92)
Observations	775	720
Adjusted R-squared	0.917	0.929
Controls	Yes	Yes
Bank Fixed Effects	Yes	Yes
Year-quarter Fixed Effects	Yes	Yes
Horizon Fixed Effect	Yes	Yes

Notes: This table reports estimates from the OLS regressions of loan loss provision on banks' loan loss forecast revisions. *NLCO_Rev* is the one-year forecast revision of the *NLCO* prediction. *LLP* is the annualized loan loss provisions (i.e., the sum of provisions in the forecast quarter and the previous three quarters) scaled by average loans outstanding. *Tier1Cap_Rev* is the forecast revision for Tier 1 capital ratio. *ROA_Rev* is the forecast revision for return on assets. *CoreRate_Rev* is the forecast revision for core deposits scaled by total assets. *Controls* include *Size*, *CapR*, *NLCO*, *Loansyield*, *FloatLoanRatio*, *Real*, and *Cons*, as defined in Appendix A. All control variables are measured in the quarter in which the forecasts are issued. Robust *t*-statistics in parentheses are based on standard errors clustered at the bank level. ***, **, * indicate statistical significance at less than 1, 5, and 10%, respectively.

Table OA2. Bank characteristics and forecast error

	(1) *NLCO_Error*
Size	0.0069
	(1.41)
CapR	0.0044
	(1.00)
NLCO	-0.0656
	(-0.99)
Loansyield	0.0020
	(0.46)
FloatLoanRatio	0.0012
	(1.71)
Real	0.0007
	(1.10)
Cons	-0.0007
	(-0.94)
Observations	2,069
Adjusted R-squared	0.071

Notes: This table reports estimates from the OLS regressions of loan loss forecast error on bank characteristics. *NLCO_Error* is the forecast error of the *NLCO* prediction. *NLCO* is the ratio of net loan charge-offs to average loans outstanding. *Size* is the natural logarithm of total assets. *CapR* is the ratio of equity to assets. *Loansyield* is the tax-equivalent interest rate on loans. *FloatLoanRatio* is the percentage of loans that reprice or mature within one year. *Real* is the proportion of real estate loans. *Cons* is the proportion of consumer loans. All explanatory variables are measured in the quarter in which the forecasts are issued. The dependent variable is constructed over nine separate horizons and then pooled. Robust *t*-statistics in parentheses are based on standard errors clustered at the bank level. ***, **, * indicate statistical significance at less than 1, 5, and 10%, respectively.

Table OA3. Representativeness heuristic in loan loss forecast, conditional on the direction of forecast revision

	(1) *NLCO_Error* (*NLCO_Rev*<0)	(2) *NLCO_Error* (*NLCO_Rev*>0)	(3) *NLCO_Error* (*NLCO_Rev*<0 Year ≤ 2019)	(4) *NLCO_Error* (*NLCO_Rev*>0 Year ≤ 2019)	(5) *NLCO_Error* (*NLCO_Rev*<0 Year ≥ 2020)	(6) *NLCO_Error* (*NLCO_Rev*>0 Year ≥ 2020)
NLCO_Rev	0.0467 (0.49)	-0.9154*** (-6.54)	-0.4206*** (-2.93)	-0.6631*** (-3.72)	0.0506 (0.34)	-0.6565** (-2.36)
Observations	420	355	333	232	86	123
Adjusted R-squared	0.432	0.712	0.375	0.478	0.670	0.754
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Horizon Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports estimates from the OLS regressions of loan loss forecast errors on loan loss forecast revisions, conditional on *NLCO_Rev*>0 vs. *NLCO_Rev*<0. *NLCO_Error* is the forecast error of the *NLCO* prediction. *NLCO_Rev* is the forecast revision of the *NLCO* prediction. Robust *t*-statistics in parentheses are based on standard errors clustered at the bank level. ***, **, * indicate statistical significance at less than 1, 5, and 10%, respectively.

Table OA4. Robustness of Table 3 to the fixed effects structure.

Panel A. Without bank fixed effects.

	(1) *NLCO_Error* (*h*=1)	(2) *NLCO_Error* (*h*=2)	(3) *NLCO_Error* (*h*=3)	(4) *NLCO_Error* (*h*=4)	(5) *NLCO_Error* (*h*=5)
NLCO_Rev	-0.4918**	-0.2222	-0.5474*	-0.5437***	-0.7310***
	(-2.31)	(-0.80)	(-1.97)	(-3.08)	(-6.44)
Observations	154	154	154	154	154
Adjusted R-squared	0.312	0.289	0.524	0.453	0.605
Bank Fixed Effects	No	No	No	No	No
Year-quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes

Panel B. Without time fixed effects.

	(1) *NLCO_Error* (*h*=1)	(2) *NLCO_Error* (*h*=2)	(3) *NLCO_Error* (*h*=3)	(4) *NLCO_Error* (*h*=4)	(5) *NLCO_Error* (*h*=5)
NLCO_Rev	-0.2818*	-0.1872	-0.7168**	-0.6979***	-0.8583***
	(-2.01)	(-0.57)	(-2.53)	(-3.63)	(-4.61)
Observations	155	155	155	155	155
Adjusted R-squared	0.495	0.160	0.463	0.436	0.532
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year-quarter Fixed Effects	No	No	No	No	No

Notes: These tables report estimates from the OLS regressions of loan loss forecast errors on loan loss forecast revisions for each forecast horizon, ranging from one quarter ahead (*h*=1) to five quarters ahead (*h*=5), after dropping bank fixed effects (Panel A) or year-quarter fixed effects (Panel B). *NLCO_Error* is the forecast error of the *NLCO* prediction. *NLCO_Rev* is the forecast revision of the *NLCO* prediction. Robust *t*-statistics in parentheses are based on standard errors clustered at the bank level. ***, **, * indicate statistical significance at less than 1, 5, and 10%, respectively.

Table OA5. Robustness of Table 4 to the fixed effects structure.

Panel A. Without bank fixed effects.

VARIABLES	(1) *NLCO_Error* (*h*=1)	(2) *NLCO_Error* (*h*=2)	(3) *NLCO_Error* (*h*=3)	(4) *NLCO_Error* (*h*=4)	(5) *NLCO_Error* (*h*=5)
NLCO_Rev (*h*=2)	-0.1598				
	(-0.84)				
NLCO_Rev (*h*=3)		-0.2752			
		(-1.07)			
NLCO_Rev (*h*=4)			-0.6492***		-0.5162***
			(-3.88)		(-3.46)
NLCO_Rev (*h*=5)				-0.6135***	
				(-4.50)	
Observations	154	154	154	154	154
Adjusted R-squared	0.073	0.318	0.554	0.477	0.520
Bank Fixed Effects	No	No	No	No	No
Year-quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes

Panel B. Without time fixed effects.

VARIABLES	(1) *NLCO_Error* (*h*=1)	(2) *NLCO_Error* (*h*=2)	(3) *NLCO_Error* (*h*=3)	(4) *NLCO_Error* (*h*=4)	(5) *NLCO_Error* (*h*=5)
NLCO_Rev (*h*=2)	-0.0764				
	(-0.54)				
NLCO_Rev (*h*=3)		-0.2881			
		(-1.27)			
NLCO_Rev (*h*=4)			-0.7663***		-0.7397***
			(-3.78)		(-3.28)
NLCO_Rev (*h*=5)				-0.7227***	
				(-6.62)	
Observations	155	155	155	155	155
Adjusted R-squared	0.402	0.246	0.490	0.469	0.417
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year-quarter Fixed Effects	No	No	No	No	No

Notes: These tables report estimates from the OLS regressions of loan loss forecast errors at a given horizon on loan loss forecast revisions at a different horizon (e.g., regressing forecast errors at one-quarter horizon, i.e., *h*=1, on forecast revisions at two-quarter horizon, i.e., *h*=2, in column 1), after dropping bank fixed effects (Panel A) or year-quarter fixed effects (Panel B). *NLCO_Error* is the forecast error of the *NLCO* prediction. *NLCO_Rev* is the forecast revision of the *NLCO* prediction. Robust *t*-statistics in parentheses are based on standard errors clustered at the bank level. ***, **, * indicate statistical significance at less than 1, 5, and 10%, respectively.

Table OA6. Robustness of Table 5 to the fixed effects structure

Panel A. Without bank fixed effects.

	(1) $NLCO\_Error_{t\|t-1}$	(2) $NLCO\_Rev\_SA_{t\|t-1}$	(3) $NLCO\_Rev\_SA_{t\|t-3}$	(4) $NLCO\_Rev\_SA_{t\|t-5}$
$NLCO\_Rev\_SA_{t\|t-1}$	-0.2852**			
	(-2.67)			
$NLCO\_Rev\_SA_{t\|t-3}$		-0.6174**		
		(-2.60)		
$NLCO\_Rev\_SA_{t\|t-5}$			-0.3887*	
			(-2.06)	
$NLCO\_Rev\_SA_{t\|t-7}$				-0.3298**
				(-2.16)
Observations	134	114	116	116
Adjusted R-squared	0.139	0.608	0.372	0.544
Bank Fixed Effects	No	No	No	No
Year-quarter Fixed Effects	Yes	Yes	Yes	Yes

Panel B. Without time fixed effects.

	(1) $NLCO\_Error_{t\|t-1}$	(2) $NLCO\_Rev\_SA_{t\|t-1}$	(3) $NLCO\_Rev\_SA_{t\|t-3}$	(4) $NLCO\_Rev\_SA_{t\|t-5}$
$NLCO\_Rev\_SA_{t\|t-1}$	-0.0593			
	(-1.06)			
$NLCO\_Rev\_SA_{t\|t-3}$		-0.8736***		
		(-4.66)		
$NLCO\_Rev\_SA_{t\|t-5}$			-0.5858***	
			(-4.10)	
$NLCO\_Rev\_SA_{t\|t-7}$				-0.4304**
				(-2.69)
Observations	135	115	117	117
Adjusted R-squared	0.402	0.623	0.154	0.041
Bank Fixed Effects	Yes	Yes	Yes	Yes
Year-quarter Fixed Effects	No	No	No	No

Notes: These tables report estimates from the OLS regressions of semi-annual NLCO forecast revision, *NLCO_Rev_SA*, estimated in quarter *t*-1, *t*-3, and *t*-5 on the same variable estimated in quarter *t*-3, *t*-5, and *t*-7, respectively, after dropping bank fixed effects (Panel A) or year-quarter fixed effects (Panel B). $NLCO\_Rev\_SA_{t|t-h}$ is the forecast made in quarter *t-h* for the *NLCO* in quarter *t* minus the forecast made in quarter *t-h*-2 for the same *NLCO* in quarter t. $NLCO\_Error_{t|t-1}$ is *NLCO* in quarter *t* minus the forecast made in quarter *t*-1 for the same *NLCO* in quarter *t*. Robust *t*-statistics in parentheses are based on standard errors clustered at the bank level. ***, **, * indicate statistical significance at less than 1, 5, and 10%, respectively.

Table OA7. Robustness of Table 7 to the fixed effects structure

Panel A. Without bank fixed effects.

	(1) *NLCO_RE_Error*	(2) *NLCO_CNI_Error*	(3) *NLCO_CO_Error*
NLCO_RE_Rev	-0.8189*** (-5.60)		
NLCO_CNI_Rev		-0.5979*** (-4.21)	
NLCO_CO_Rev			-0.4644*** (-3.58)
Observations	775	775	775
Adjusted R-squared	0.496	0.419	0.382
Bank Fixed Effects	No	No	No
Year-quarter Fixed Effects	Yes	Yes	Yes
Horizon Fixed Effect	Yes	Yes	Yes

Panel B. Without time fixed effects.

	(1) *NLCO_RE_Error*	(2) *NLCO_CNI_Error*	(3) *NLCO_CO_Error*
NLCO_RE_Rev	-0.7141*** (-13.64)		
NLCO_CNI_Rev		-0.6618*** (-7.11)	
NLCO_CO_Rev			-0.7084*** (-6.62)
Observations	775	775	775
Adjusted R-squared	0.722	0.390	0.331
Bank Fixed Effects	Yes	Yes	Yes
Year-quarter Fixed Effects	No	No	No
Horizon Fixed Effect	Yes	Yes	Yes

Panel C. Without fixed effects.

	(1) *NLCO_RE_Error*	(2) *NLCO_CNI_Error*	(3) *NLCO_CO_Error*
NLCO_RE_Rev	-0.7424***		
	(-6.67)		
NLCO_CNI_Rev		-0.6817***	
		(-7.06)	
NLCO_CO_Rev			-0.5490***
			(-4.15)
Observations	775	775	775
Adjusted R-squared	0.419	0.342	0.171
Bank Fixed Effects	No	No	No
Year-quarter Fixed Effects	No	No	No
Horizon Fixed Effect	No	No	No

Notes: These tables report estimates from the OLS regressions of loan loss forecast errors on their corresponding forecast revisions for different loan types, after dropping bank fixed effects (Panel A), year-quarter fixed effects (Panel B), or all fixed effects (Panel C). *NLCO_RE_Error, NLCO_CNI_Error, and NLCO_CO_Error (NLCO_RE_Rev, NLCO_CNI_Rev, and NLCO_CO_Rev) are forecast errors (revisions) of loan losses for real estate loans, commercial and industrial loans, and consumer loans, respectively*. Forecast error and forecast revision of all loan types are defined in the same way as *NLCO_Error* and *NLCO_Rev*. Robust *t*-statistics in parentheses are based on standard errors clustered at the bank level. ***, **, * indicate statistical significance at less than 1, 5, and 10%, respectively.

Table OA8. Robustness of Table 8 to the fixed effects structure

Panel A. Without bank fixed effects.

	(1) *NLCO_Error* Year ≤ 2017	(2) *NLCO_Error*	(3) *NLCO_Error*	(4) *NLCO_Error*
NLCO_Rev	-0.5103*** (-3.01)	-0.5847*** (-3.14)	-0.6048*** (-3.92)	-0.2888* (-1.84)
*NLCO_Rev*Year2018*		0.4570** (2.61)		
*NLCO_Rev*Year2019*			1.3251*** (10.64)	
*NLCO_Rev*Year2020*				-0.5613*** (-3.80)
Observations	305	775	775	775
Adjusted R-squared	0.243	0.467	0.496	0.502
Bank Fixed Effects	No	No	No	No
Year-quarter Fixed Effects	Yes	Yes	Yes	Yes
Horizon Fixed Effect	Yes	Yes	Yes	Yes

Panel B. Without time fixed effects.

	(1) *NLCO_Error* Year ≤ 2017	(2) *NLCO_Error*	(3) *NLCO_Error*	(4) *NLCO_Error*
NLCO_Rev	-0.5629*** (-5.97)	-0.6510*** (-3.34)	-0.6706*** (-3.84)	-0.2014 (-1.23)
*NLCO_Rev*Year2018*		0.1427 (0.48)		
*NLCO_Rev*Year2019*			0.6914*** (5.02)	
*NLCO_Rev*Year2020*				-0.8456*** (-6.00)
Observations	305	775	775	775
Adjusted R-squared	0.529	0.445	0.454	0.563
Bank Fixed Effects	Yes	Yes	Yes	Yes
Year-quarter Fixed Effects	No	No	No	No
Horizon Fixed Effect	Yes	Yes	Yes	Yes

Panel C. Without fixed effects.

	(1) *NLCO_Error* Year ≤ 2017	(2) *NLCO_Error*	(3) *NLCO_Error*	(4) *NLCO_Error*
NLCO_Rev	-0.5048*** (-3.06)	-0.7009*** (-3.77)	-0.7162*** (-4.57)	-0.2266 (-1.56)
*NLCO_Rev*Year2018*		0.5364** (2.57)		
*NLCO_Rev*Year2019*			1.3022*** (14.74)	
*NLCO_Rev*Year2020*				-0.8618*** (-6.91)
Observations	305	775	775	775
Adjusted R-squared	0.253	0.318	0.345	0.436
Bank Fixed Effects	No	No	No	No
Year-quarter Fixed Effects	No	No	No	No
Horizon Fixed Effect	No	No	No	No

Notes: These tables report estimates from the OLS regressions of loan loss forecast errors on loan loss forecast revisions, after dropping bank fixed effects (Panel A), year-quarter fixed effects (Panel B), or all fixed effects (Panel C). Column 1 only includes forecasts made during 2014-2017. Column 2 (3, 4) uses the full sample and includes the interaction between forecast revision and an indicator of 2018 (2019, 2020). *NLCO_Error* is the forecast error of the *NLCO* prediction. *NLCO_Rev* is the forecast revision of the *NLCO* prediction. Robust *t*-statistics in parentheses are based on standard errors clustered at the bank level. ***, **, * indicate statistical significance at less than 1, 5, and 10%, respectively.