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Climate beliefs, attitudes, and bank risk management

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ABSTRACT

We investigate the relationship between climate beliefs and attitudes (CBA) and bank risk management. We find that county-level CBA is positively associated with bank loan loss reserves (ALL) and provisions (LLP), suggesting that banks set aside higher reserves to cushion potential losses when managers believe in climate change. Further analyses using multiple approaches indicate that CBA has incremental explanatory power over climate risk in influencing ALL and LLP—this is an important insight since prior banking literature has mainly focused on climate risk. Our results are robust to various checks, and we show that CBA is negatively related to bank loan portfolio risk and overall bank risk-taking. In consequence tests, we document that CBA attenuates the positive relationship between climate risk and bank risk. Our study suggests that CBA is a behavioral impetus for bank managers to be more prudent in managing climate risk exposures via conservative loan loss accounting.

1. Introduction

A significant portion of the population remains unconvinced about the negative impacts of climate change and the role of human activities in driving it. This skepticism is considered a key hurdle in initiating actions to mitigate consequences related to climate change (e.g., Hornsey et al., 2016). For example, the 2021 Yale Climate Opinion Maps (YCOM) survey suggests that only 57% of adults in the U.S. think "global warming is caused by humans," and 64% think "global warming is affecting the weather."[1] These climate change beliefs and attitudes (hereafter, CBA) are crucial in determining the effectiveness of climate-related policies (Lorenzoni and Pidgeon, 2006; Howe et al., 2015) and in influencing individuals' and corporations' climate risk mitigation behaviors (Mase et al., 2017; Aghion et al., 2023; Zhang et al., 2024). Despite increased concern about climate change in the U.S. following disastrous climate events (Rogelj et al., 2014; Goldberg et al., 2020), few studies have examined the influence of CBA on banks' loan loss accounting and risk management practices.

Prior banking research on climate finance has primarily explored the impact of natural disasters and climate risk on credit supply and lending (e.g., Cortés and Strahan, 2017; Dessaint and Matray, 2017; Kacperczyk and Peydro, 2022; Nguyen et al., 2022; Morse and Sastry, 2024; Dursun-de Neef and Ongena, 2025).[2] However, few studies examine how climate change beliefs and attitudes, independent of climate risk, shape corporate decisions. Recent work (e.g., Cialdini and Jacobson, 2021; Bergquist et al., 2023; Erten and Onega, 2024; Zhang et al., 2024) highlights social norms as a key driver of climate-related corporate decision-making. Building on this, we investigate the influence of climate-related beliefs and attitudes (CBA) on risk management through bank loan loss accounting practices.

We focus on banks' allowance for loan losses (ALL) and loan loss provisions (LLP). ALL is the reserve set aside for future credit losses, while LLP adds to ALL to cover estimated credit losses. LLP has nondiscretionary and discretionary components: the former addresses foreseeable losses, while the latter reflects managerial discretion (e.g., Wahlen, 1994; Kanagaretnam et al., 2004). The cumulative discretionary LLP contributes to 'abnormal' ALL levels. Studies find abnormal LLP and ALL improve risk discipline (Bushman and Williams, 2002; Jin et al., 2018) and can signal better credit risk management and conservative loan loss recognition (e.g., Bhat et al., 2019; Dal Maso et al., 2024).

We examine the relationship between CBA and bank loan loss

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[1] Survey results can be accessed at: https://climatecommunication.yale.edu/visualizations-data/ycom-us/

[2] Recent research also examines investor reactions to climate risk (e.g., Bolton and Kacpercyzk, 2022; Ilhan et al., 2023)

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accounting by constructing a county-level measure of CBA at the bank's headquarters level using the first principal component from a factor analysis of three variables from the county-level survey conducted by the Yale Program on Climate Change Communication (YPCCC) during 2014-2021 (Howe et al., 2015; Marlon et al., 2022). Following prior literature (e.g., Pirinsky and Wang, 2006; Hilary and Hui, 2009), we define a bank's location as the county in which its headquarters is located. As noted by Pirinnsky and Wang (2006), this approach seems "reasonable given that corporate headquarters are close to corporate core business activities". In particular, credit risk management, including decisions on overall loan loss provisions, is made at the headquarters level rather than at the local branch level.

We posit that CBA is positively related to LLP and ALL (or conservative loan loss accounting in the sense of higher reserves), primarily due to bank stakeholders' varying awareness and perceptions of climate change, rather than the climate risk itself, from both supply and demand side reasons. From the supply side, existing literature suggests that people who are more concerned about the environment's vulnerability (i.e., the belief) and who place a higher value on protecting the environment (i.e., the attitude) are more likely to recognize climate change threats and engage in actions to mitigate these risks (e.g., Schwartz, 1994; Stern et al., 1995; Hornsey et al., 2016). Such climate change beliefs and attitudes can shape a socially shared perception (or a 'social norm') regarding the mitigation of climate risk. Influenced by the desire to conform to local social norms, bank managers in areas with higher CBA will be more likely to take precautions against adverse climate events (Deutsch and Gerald, 1955; Willer et al., 2009; Horne and Kennedy, 2017). In this vein, we argue that CBA can influence the behavioral patterns of bank managers and employees (e.g., Kumar et al., 2011; McGuire et al., 2012), making them more conservative in their reporting choices to build reserves to absorb shocks from unexpected climate events. From the demand side, regulators in areas with higher CBA may require more conservative firm policies to hedge against climate events.[3] Similarly, bank investors and depositors in higher CBA regions will likely be more risk-averse when making investment decisions, leaning towards banks that are more resilient to adverse climate events. In response, banks may adopt more conservative policies to minimize compliance costs and liabilities and to align with investor expectations.

Conservative bank loan loss accounting can be an effective way for banks to hedge against unexpected climate events.[4] For example, Dal Maso et al. (2024) find that banks in U.S. counties with higher disaster risk report higher LLP, implying that banks proactively manage climate risks with enhanced credit risk management through conservative loan loss accounting. We bring in the dimension of CBA and argue that, even without frequent adverse climate events, banks will be more proactive in climate risk management and have conservative loan loss accounting practices if managers have higher CBA.

However, our prediction is not without tension. First, climate beliefs may be secondary to climate risk. If this is the case, climate beliefs would be subsumed by climate risk, and their marginal influence on conservative loan loss accounting would be minimal, thereby limiting the insights of our paper. Second, climate beliefs may not be as salient in highly regulated industries like banking. Regulatory mandates, such as the OCC's emphasis on climate risk management, may overshadow the role of climate beliefs in influencing conservative loan loss accounting due to stringent regulatory requirements.[5]

In our main analysis, we test the relationship between CBA and LLP (ALL) during 2014-2021: consistent with our prediction, we find that CBA is positively related to LLP (ALL) using various model specifications. This effect is also economically significant: using coefficients estimated in baseline models, a one-standard-deviation increase in lagged CBA is associated with a 14.92% (1.54%) increase in LLP (ALL). In addition, we conduct several tests to address concerns that regional climate risk may confound the relationship between CBA and conservative loan loss accounting. Using univariate comparisons across climate risk groups, a two-stage residual approach that removes climate risk and demographic effects, and subsample regressions by climate risk exposure, we consistently find that higher CBA is associated with more conservative loan loss accounting, even after controlling for regional climate conditions, macroeconomic conditions, and demographics.

Furthermore, we employ a series of additional robustness tests to further validate our main findings. First, we implement the reverse causality minimization approach (Godfrey et al., 2024). We decomposed CBA into fitted and residual components based on lagged LLP. The residual component of CBA—which is orthogonal to past provisioning—remains significantly positively related to LLP and ALL. Second, we ran Oster (2019) tests to evaluate the potential influence of omitted variable bias. The results ($\delta = 9.30$ for LLP and 5.83 for ALL) suggest that unobserved confounders would need to be 9.3 and 5.8 times more influential than observed controls to overturn our findings, largely alleviating the omitted variable bias concern. Third, we perform two subsample tests: (1) restricting the sample to banks with higher geographic deposit concentration, and (2) splitting the sample into pre- and post-COVID-19 periods. The results remain consistent in these subsample tests. Finally, we employ two alternative measures of CBA and three distinct proxies for climate risk and continue to find consistent results.

Next, we explore whether and how CBA influences bank risk-taking. We measure bank risk-taking from two perspectives, namely, bank loan portfolio risk-taking and bank overall risk-taking. First, following Lee et al. (2024), we measure bank loan portfolio risk-taking with an accounting-based equity-to-loan portfolio risk measure (ELPR) that captures the cross-correlations in default rates between different types of loans. We then take the negative of ELPR (NELPR), so that a higher NELPR indicates higher risk-taking.[6] Second, we measure overall bank risk-taking using the Z-score and volatility of the net interest margin.[7] Using these measures, we find that CBA is significantly negatively associated with bank risk-taking, indicating managers' climate awareness is associated with more cautionary business practices. In terms of economic significance, a one-standard-deviation increase in CBA is associated with a 1.1%, 0.57%, and 3.47% decrease in bank loan portfolio risk-taking, Z-score, and volatility of net interest margin, respectively.

To close the loop of inference, we examine whether the proactive stance in risk management influenced by CBA could mitigate the impact of climate risks on the banks' overall risk profile. Consistent with Dal Maso et al. (2024), we construct a measure of climate risk as the changes in the count of natural disasters designated as 'major' by the Federal Emergency Management Agency (FEMA) over a 15-year period for each quarter in U.S. counties. Our test results are consistent with our

[3] Regional regulators increasingly recognize climate change as a significant source of credit risk. For example, New York State Department of Financial Services promote the regulation of climate-change-related credit risk for banks (source: https://www.dfs.ny.gov/reports_and_publications/press_releases/pr202111032)

[4] Banks can adopt other risk mitigation strategies, such as incorporating climate risk into lending decisions and insurance protection. However, as discussed in Dal Maso et al. (2024), the pricing of climate risk can be challenging and that climate risk, such as disaster risk, is mostly uninsurable.

[5] For example, the Office of the Comptroller of the Currency (OCC) and the Federal Reserve Board have outlined several principles for managing climate-related financial risks (OCC, 2023).

[6] This measure is calculated as the natural logarithm of adjusted book value of equity to the constructed loan portfolio risk measure. We then take the negative so that the higher the measure, the higher the risk-taking. Detailed description of this measure is provided in Section 3.3.

[7] The detailed description of the construction of Z-score and volatility of net interest margin is provided in Section 3.3 and in Appendix A.

predictions: in baseline tests, we find that bank risk is significantly positively associated with climate risk, as expected. In a cross-sectional test, we find that the sensitivity of bank risk to climate risk is significantly lower in county-years with a higher level of CBA than in those with a lower level of CBA.[8]

We contribute to the literature in several important ways. First, our paper extends studies related to climate awareness. Although there exists an increasing number of studies on the importance of climate awareness for climate-change-related behaviors (e.g., Spartz et al., 2017; Cialdini and Jacobson, 2021; Nolan, 2021; Sparkman et al., 2021), surprisingly few studies have examined the impact of CBA on the behaviors of corporations and the associated economic impacts. Some exceptions include, for example, Zhang et al. (2024) and Aghion et al. (2023). Zhang et al. (2024) find that a climate change social norm is positively associated with corporate cash holdings. Aghion et al. (2023) examine the automobile sector and find that firms' exposure to pro-environmental and social attitudes facilitates Green innovation. Erten and Ongena (2024) show that environmental risk pricing in bank lending is also driven by local beliefs and attitudes. Extending these studies, we focus on banks, whose lending portfolios can be notably susceptible to climate risks faced by their borrowers. We not only document that CBA is a significant determinant of banks' prudential loan loss provisioning practices, but also show that banks are less susceptible to climate risk when the level of CBA is higher. Given that past literature has focused extensively on the influence of climate risk on bank risk management, our results showing the incremental explanatory power of CBA are noteworthy. This is even more significant, given many alternative specifications and multiple measures of climate risk we employ in the analyses. Second, our study builds on the extensive body of research on bank financial accounting that examines the factors influencing bank loan loss provisioning practices (e.g., Kanagaretnam et al., 2004, 2014; Hribar et al., 2017; Nicoletti, 2018). We expand this area of research by identifying CBA as a novel factor affecting conservative bank loan loss provisioning. Third, our work adds to the wide-ranging research, on the impact of social beliefs and attitudes on economic behaviors, which focuses on factors like societal trust, religion, and gambling attitudes (Hilary and Hui, 2009; Kumar et al., 2011; El Ghoul et al., 2012; Callen and Fang, 2015). Our research concentrates on the influence of social beliefs and attitudes about climate risk on bank loan loss accounting practices and related risk management. To our knowledge, this is the first empirical investigation into the influence of CBA on bank risk management practices.

The rest of this study is organized as follows. We develop our hypotheses in Section 2, present the data and research design in Section 3, discuss the empirical results in Section 4, and make concluding remarks in Section 5.

2. Related literature and hypotheses development

2.1. Climate change beliefs and attitudes

Human-induced climate change poses a significant threat to life on Earth and future generations; this consensus, highlighted in studies like Hayward (2012) and Popovski and Mundy (2012), underscores the responsibility of humanity to engage in both mitigation and adaptation strategies regarding climate change. However, a significant portion of people remain skeptical about human-induced climate change and the value of mitigation efforts (e.g., Pidgeon, 2012; Rode et al., 2021). Based on existing studies, climate change beliefs and attitudes can be referred to as perspectives and perceptions that individuals hold regarding the anthropogenic causes of climate change and the associated negative consequences (Leiserowitz, 2006; Kahan et al., 2012; Rode et al., 2021). These beliefs and attitudes are shaped by a combination of psychological, cultural, and socio-political factors, influencing public support for environmental policies and personal/firm behavioral changes.

Prior literature suggests that environment-related beliefs and attitudes influence a wide range of behaviors such as the establishment of mitigation and adaptation policies regarding climate change (e.g., Lorenzoni and Pidgeon, 2006; Howe et al., 2015; Mase et al., 2017), energy consumption patterns (e.g., Horne and Kennedy, 2017), energy conservation (e.g., Allcott, 2011), recycling (e.g., Sorkun, 2018), and other pro-environmental behaviors (e.g., Cialdini et al., 1990; Cialdini and Jacobson, 2021). A growing body of literature examines the factors that shape CBA and its various impacts. On determinants of CBA, for example, Howe et al. (2015) observed a wide range of variations in the belief in climate change across the U.S., depending on factors such as education, political ideology, and demographics. On the economic consequences of CBA, Mase et al. (2017) find that CBA motivates Midwestern U.S. farmers to follow climate change adaptation measures. Zhang et al. (2024) document that a climate change social norm is positively associated with corporate cash holdings, a potential mechanism through which the climate change social norm influences corporate social responsibility (CSR) performance. Aghion et al. (2023) use patents of automobile sector firms in an international setting and find that firms' exposure to pro-social or pro-environmental attitudes promotes green innovation. Erten and Ongena (2024) document that banks charge higher rates to firms creating more environmental damage, especially when they are lowly capitalized, and when the firms operate in "greener" states with lower climate denial, and there is more negative environmental news.

2.2. Bank loan loss accounting

LLP is a set-aside expense that adds to ALL to cover anticipated uncollectible loans. It gives financial institutions a cushion against expected future loan charge-offs. LLP represents the largest accrual in banks' financial reports. According to Beatty and Liao (2014), the mean absolute value of LLP is about 56% of total bank accruals, which is about twice as much as the next largest accrual. Due to its forward-looking nature, LLP allows for managerial discretion. Previous studies have divided LLP into nondiscretionary and discretionary components (e.g., Wahlen, 1994; Kanagaretnam et al., 2004, 2010). The nondiscretionary part anticipates immediate and imminent credit losses, while the discretionary part reflects management's discretion. In this sense, the cumulative effect of discretionary LLP builds up an abnormal amount of ALL.

Indeed, bank managers can influence the timing of LLP recognition in financial statements by adjusting the discretionary portion of LLP (e.g., Ng et al., 2020). The discretionary portion can be further categorized into two types based on the managers' underlying motivations (e.g., Lobo, 2017). The first type involves efficiency-oriented discretion, by which managers might utilize LLP to convey private information, smooth income to lower perceived risk, or secure external financing (e.g., Kanagaretnam et al., 2004; Liu and Ryan, 2006; Fonseca and Gonzalez, 2008). The second type is the use of discretion for opportunistic purposes, by which managers might use LLP to meet or beat earnings benchmarks, boost reported income, or improve job security (e.g., Beatty et al., 2002; Kanagaretnam et al., 2003).

2.3. Hypotheses development

We posit that CBA is positively associated with abnormal LLP and abnormal ALL through enhanced climate-risk-related credit risk management, from both the supply and demand sides.

On the supply side, we posit that both bank managers and employees would be more willing to engage in climate risk mitigation via conservative loan loss accounting if they work in regions with higher levels of

[8] In untabulated tests, we also document that our results are robust to the use of different estimation windows of Z-score and the use of a weighted bank branch exposure (across counties, by deposits) measure of climate risk.

CBA. Schwartz (1977) argues that, through the internalization of feelings of moral obligation, personal altruistic behavior is positively affected by personal norms, which are shaped by social-level perceptions, attitudes, and beliefs (i.e., social norms). In this sense, managers and employees living in areas with higher levels of CBA are more likely to make efforts to manage climate risk by hedging against unexpected climate events because CBA is an important element of the social environment where managers live and operate (e.g., Sunstein, 1996; Yonker, 2017). Even if managers and employees themselves do not believe in climate change, the significant social influence imposed by the CBA in their area can still affect them (Deutsch and Gerald, 1955; Willer et al., 2009; Horne and Kennedy, 2017). Considering that loan loss reserves function as a cushion against future loan losses, which may be caused by unexpected climate-related events, we predict that managers and employees in high CBA regions are more likely to recognize more loan loss provisions and build a higher level of loan loss reserves.

On the demand side, some regional bank regulators increasingly acknowledge that climate change is a major source of credit risk that affects both the creditworthiness of borrowers and the value of loan collateral (e.g., Steele, 2020). For example, the New York State Department of Financial Services has issued multiple Industry Letters expecting banks to address financial risks from climate change[9] and established a new Climate Division[10] in 2021 tasked with integrating climate risks into the supervision of regulated entities. We predict that local regulators in higher CBA regions will be more stringent in demanding enhanced credit risk management related to climate change. In addition, other stakeholders, such as depositors, creditors, and shareholders, can also have a higher awareness of climate-change-related risks in higher CBA regions and hence demand more conservative credit risk management from banks. As aforementioned, one effective strategy for banks to build resilience to unexpected adverse climate events is through prudential loan loss provisioning (Dal Maso et al., 2024). We suggest that banks in high CBA regions are more motivated to build extra cushions to absorb future loan losses due to unexpected adverse climate events through conservative loan loss accounting.

Based on the above discussion and prior findings, we propose the following hypothesis:

H1. CBA is positively related to abnormal LLP and abnormal ALL

However, our prediction is not without tension. First, climate beliefs may be secondary to climate risk. Several existing studies find that climate risk has a first-order effect on firms' climate risk management. For example, Huang et al. (2022) document that firms that actively manage climate risk are more successful in reducing the adverse impacts of climate risk on loan contracting. Dal Maso et al. (2024) find that disaster risk is positively related to banks' credit risk management. If climate beliefs influence banks' conservative loan loss accounting via climate risk, we would observe a high correlation between CBA and climate risk and an insignificant marginal impact of CBA on conservative bank loan loss accounting. Second, in highly regulated industries such as banking, climate beliefs may not be as salient. National level regulatory mandates, such as the OCC's emphasis on climate risk management, may overshadow the role of climate beliefs in influencing conservative loan loss accounting due to stringent regulatory requirements. For instance, the OCC's recent guidelines (2023) stress the importance of integrating climate risk into overall risk management frameworks, which could oblige banks to adopt conservative loan loss accounting practices irrespective of their internal climate beliefs. In this vein, we may not observe any tangible relationship between CBA and conservative bank loan loss accounting.

[9] Source: https://www.dfs.ny.gov/industry_guidance/climate_change

[10] Source: https://www.dfs.ny.gov/reports_and_publications/press_releases/pr202111032

In addition, as we expect that banks in areas with higher levels of CBA are more proactive in mitigating climate and related risks, these banks should exhibit reduced risk-taking behaviors both at the loan level (i.e., lower loan portfolio risk) and at the overall bank-level (i.e., more stable earnings). Therefore, we also propose the following hypothesis:

H2. CBA is negatively related to both bank loan portfolio risk and overall bank risk

To close the loop of inference, we make an additional hypothesis. A plausible outcome of our prediction that CBA positively influences conservative loan loss accounting, driven by increased awareness and perception of climate risk, is a reduced correlation between overall bank risk and climate risk in banks situated in counties with higher CBA levels. These banks are expected to proactively address potential climate risks, influenced by CBA, by enhancing their credit risk management through prudential loan loss provisioning practices (e.g., Dal Maso et al., 2024) and other related initiatives. This proactive stance in risk management should mitigate the impact of climate risks on the banks' overall risk profile. Hence, we propose the following hypothesis:

H3. The sensitivity of bank risk to climate risk is attenuated by CBA

3. Research design

3.1. Measures of CBA

Our primary measure of county-level CBA is constructed from the county-level YCOM survey conducted by the YPCCC from 2014 to 2021. Following prior literature (e.g., Pirinsky and Wang, 2006; Hilary and Hui, 2009), we define a bank’s location as the county in which its headquarters is located. We follow this approach since major decisions by senior management on core activities and risk management are most likely made at the bank headquarters. In particular, overall loan loss provisions are made at the headquarters level rather than at the local branch level. As robustness checks, we limit the sample to banks whose branch deposits are 100% or 90% in a single county (small banks) and our results hold.

The YCOM survey asks questions on multiple dimensions of climate change opinions, including beliefs, risk perceptions, policy support, and behaviors (Howe et al., 2015; Marlon et al., 2022). In this measure, we follow Zhang et al. (2024) and choose three umbrella questions that are consistent with climate change beliefs and attitudes. The questions include 1) the estimated percentage of respondents who are somewhat/very worried about global warming, 2) the estimated percentage of respondents who think that global warming is happening, and 3) the estimated percentage of respondents who think global warming will harm people in the U.S. a moderate amount/a great deal. We compute CBA as the first principal component extracted from a principal component analysis (PCA) of these three variables. The first factor has an eigenvalue of 2.83.[11] We estimate CBA annually for 2014-2021 (excluding 2015 and 2017 due to missing survey results) using the three standardized variables with mean values equal to 0 and standard deviation equal to 1.

We use this survey data for the following reasons. Existing studies, such as Cialdini et al. (1990), Hilary and Hui (2009), and Kumar et al. (2011), use survey data to measure regional social perceptions, beliefs, and attitudes. CBA refers to social perceptions, beliefs, and attitudes related to climate change. In addition, Zhang et al. (2024) is the first study to utilize survey data to measure climate-change-related social

[11] This translates to a normalized eigenvalue of 0.9417, suggesting that 94% of the total variance in the selected core climate questions is captured by the first principal component. Analogously, our alternative measure of CBA (the first principal component of 12 survey variables) has a normalized eigenvalue of 0.75.

perceptions, beliefs, and attitudes, in which three umbrella questions from the YCOM survey data are used to construct county-level CBA from 2014 to 2020.

As robustness checks, we also use two alternative measures, all based on the YCOM survey data. To construct our first alternative measure, we choose all 12 variables with available data from 2014 to 2020 (excluding 2015 and 2017) that cover the four dimensions of the survey questions. This measure (denoted as *CBA_ALT*) is calculated as the first principal component extracted from a principal component analysis of these variables. The variables include, for example, the estimated percentage of respondents who think that global warming is happening, the estimated percentage of respondents who are worried about global warming, the estimated percentage of respondents who support regulating CO2 as a pollutant, and the estimated percentage of respondents who discuss global warming occasionally or often with friends and family.[12] Our second alternative measure is the bank-branch-exposure-weighted CBA (*CBA_WTD*): for banks that operate in multiple counties, their CBA is calculated as the weighted average CBA across these counties based on the dollar amount of branch deposits in these counties. We obtain the branch deposit data from the FDIC's Summary of Deposits (SOD) database.

3.2. Measures of climate risk

Following Dal Maso et al. (2024), we measure climate risk (denoted as *CRISK*) using the number of past natural disaster events declared as major disasters by the Federal Emergency Management Agency over a 15-year span for each U.S. County in each quarter. OECD (2015) suggests that the past events recorded in the FEMA dataset could capture the level of hazard, exposure, and vulnerability of geographical regions. Moreover, because the disaster risk has spatial and temporal attributes, we choose a relatively narrow 15-year span to account for each county's more temporally adjacent natural disaster events (e.g., UNDRR, 2019; UNISDR, 2015). In addition, according to the Robert T. Stafford Disaster Relief and Emergency Assistance Act 2 U.S.C. §§ 5121–5207, which regulates the FEMA Disaster Declaration Process, only relatively large disasters that affect local economies materially are included.

3.3. Baseline regression model

Following the banking literature (Kanagaretnam et al., 2010; Beatty and Liao, 2014; Chen et al., 2018; Basu et al., 2020), we employ the following empirical model:

$$\begin{aligned} LLP_{it} = {} & \alpha_0 + \alpha_1 CBA_{i,t-1} + \alpha_2 CRISK_{i,t-1} + \alpha_3 ALL_{i,t-1} + \alpha_4 NPL_{i,t-1} \\ & + \alpha_5 LOANS_{i,t} + \alpha_6 \Delta LOAN\%_{i,t} + \alpha_7 NCO_{i,t} + \alpha_8 \Delta NPL_{i,t} \times \Delta NPL_{i,t} \\ & + \alpha_9 \Delta NPL_{i,t} + \alpha_{10} D\Delta NPL_{i,t} + \alpha_{11} V + \alpha_{12} W + County\ FE \\ & + Quarter\ FE + \varepsilon_{i,t} \end{aligned} \tag{1}$$

where $LLP_{i,t}$ is the loan loss provisions scaled by lagged total loans, $CBA_{i,t-1}$ is the lagged measure of climate change social norms at the county-year level. $ALL_{i,t-1}$ is the previous period's allowance for loan losses scaled by lagged total loans, $LOANS_{i,t}$ is total loans scaled by lagged total assets, $\Delta LOAN\%_{i,t}$ denotes the percentage change in *LOANS* during the quarter, $NCO_{i,t}$ is net charge-offs (which is calculated as charge-offs minus recoveries), $\Delta NPL_{i,t}$, $\Delta NPL_{i,t-1}$ denotes changes in nonperforming loans in the current and previous period. $D\Delta NPL_{i,t}$ is a dummy variable equal to 1 if the sign of $\Delta NPL_{i,t}$ is negative, which captures the V-shaped relationship between *LLP* and *ΔNPL* (Basu et al., 2020). *V* is a vector of additional bank characteristics. *W* is a vector of macroeconomic characteristics. *County FE* and *Quarter FE* represent bank and year-quarter fixed effects.

We select bank-level control variables (captured by *V* in Eq. (1)) that prior studies document are associated with the abnormal portion of ALL or LLP. We control for the lagged natural logarithm of total assets ($SIZE_{i,t-1}$); prior literature documents that bank managers' incentive to convey private information via discretionary loan loss provisioning is negatively related to bank size, because larger banks can have a lower degree of information asymmetry, hence require less private information signaling (e.g. Kanagaretnam et al., 2005). We control for lagged tier 1 capital ratio ($TIER1_{i,t-1}$) because studies document that bank managers are motivated to use LLP to circumvent capital adequacy requirements (Beatty and Liao, 2014). We control for earnings before tax and LLP scaled by lagged total loans ($EBTLLP_{i,t}$) to control for bank managers' incentives to use LLP to smooth income (e.g., Kanagaretnam et al., 2004; Bushman and Williams, 2012). Moreover, $RESRELNS_{i,t}$, $FMRELNS_{i,t}$, $AGLNS_{i,t}$, $CILNS_{i,t}$, and $CSLNS_{i,t}$ represent the proportion of different types of loans, which are used to capture any differences in discretionary loan loss provisioning due to different specializations of banks—they represent the proportion of residential real estate loans, proportion of farm real estate loans, proportion of agricultural loans, proportion of commercial and industrial loans, and proportion of consumer loans, respectively. In addition, we control for any differences in discretionary loan loss provisioning incentives due to different macroeconomic outlooks and predictions by controlling for the change in the natural logarithm of county-level GDP ($\Delta GDP_{i,t}$) and change in county-level unemployment rate ($\Delta UNEMP_{i,t}$), as well as the lagged values of county-level GDP ($GDP_{i,t-1}$), county-level education attainment (EDU_{t-1}), and county-level marital status ($MARITAL_{i,t-1}$). We provide detailed definitions of all the variables in Appendix A.

Next, following Beck and Narayanamoorthy (2013) and Jin et al. (2018), we use the following loan loss allowances model to test the relationship between ALL and CBA:

$$\begin{aligned} ALL_{i,t} = {} & \beta_0 + \beta_1 CBA_{i,t-1} + \beta_2 CRISK_{i,t-1} + \beta_3 AVENCO_{i,t} + \beta_4 NPL_{i,t} \\ & + \beta_5 NPL_{i,t-1} + \beta_6 SIZE_{i,t-1} + \beta_7 TIER1_{i,t-1} + \beta_8 LOANS_{i,t} \\ & + \beta_9 \Delta LOAN\%_{i,t} + \beta_{10} ALL_{i,t-1} + \beta_{11} EBTLLP_{i,t} + \beta_{12} LoanComp \\ & + \beta_{13} W + County\ FE + Quarter\ FE + \varepsilon \end{aligned} \tag{2}$$

where $AVENCO_{i,t}$ is the past four quarters' average net charge-offs (*NCO*) scaled by lagged total loans, *LoanComp* represents the five variables mentioned earlier that represent the proportion of different types of loans (i.e., *RESRELNS, FMRELNS, AGLNS, CILNS*, and *CSLNS*). All other variables in Eq. (2) are described in the variable explanation paragraph for Eq. (1).

3.4. Measures of bank loan portfolio risk and overall bank risk

We measure banks' loan portfolio risk-taking following Lee et al. (2024), who introduced an accounting-based equity-to-loan portfolio risk (ELPR) measure that complementarily predicts bank failure up to five years in advance. ELPR is constructed as the natural logarithm of the adjusted book value of equity over loan portfolio risk (LPR), where LPR captures the temporal variation of the cross-correlations in default rates between different types of bank loans and reflects a one-standard-deviation move in the dollar amount of default losses for a bank's loan portfolio. Consistent with Lee et al. (2024), we construct LPR by estimating a 14 × 14 variance-covariance matrix ($\boldsymbol{\Omega}$) of default rates in each of the 14 loan categories using FDIC Quarterly Banking Profile (QBP) data from the first quarter of 1991 to the third quarter of 2023 (all available data). We then estimate a 1 × 14 vector ($\boldsymbol{\theta}$) of a bank's holdings

[12] See Appendix B for a full list of the 12 variables.

in each of the 14 loan categories for each bank-quarter using call data.[13] We calculate LPR as the square root of $\boldsymbol{\theta} \times \boldsymbol{\Omega} \times \boldsymbol{\theta}^{\mathbf{T}}$. Last, we use the negative of ELPR (denoted as *NELPR*), so that the higher the *NELPR*, the higher the bank loan portfolio risk-taking.

Moreover, we measure banks' overall level of risk-taking with two proxies, namely, the negative natural logarithm of Z-score (*ZSCORE*) and the volatility of NIM (σNIM), both of which are estimated with a window of four quarters.[14] σNIM is measured by taking the standard deviation of net interest margin over a span of the past four quarters. Z-score is defined as the sum of return on assets (ROA) and capital-asset ratio, divided by the standard deviation of ROA; it measures the number of standard deviations a bank's ROA has to fall before insolvency (e.g., Laeven and Levine, 2009; Demirgüç-Kunt and Huizinga, 2010; Beck et al., 2013; Kanagaretnam et al., 2014; Goetz, 2018). Since the Z-score is highly skewed, we use the natural logarithm of the Z-score. We then multiply the log of the Z-score by -1, so that the higher the measure, the greater the bank risk-taking.

4. Results

4.1. Sample

We obtain data on climate change beliefs and attitudes from YCOM, quarterly bank accounting data from Call Reports, bank branch deposits data from the SOD database, climate disaster risk data from FEMA, loan default risk data from FDIC QBP, GDP data from the U.S. Bureau of Economic Analysis, unemployment rate data from U.S. Bureau of Labor Statistics, and demographics data from U.S. Census Bureau.[15] To construct our sample, we start with quarterly Call Report data from 2005 to 2021 and then exclude observations with no county data, no FDIC certificate number, or no invalid state name, and restrict our sample to the banks in the contiguous U.S. and Alaska. Then, we exclude observations with negative or missing total assets, missing loan loss provisions, missing allowances for loan losses, and missing total loans. After that, we merge the Call data with CBA data, bank branch deposits data, disaster risk data, loan default risk data, macroeconomics data, and demographics data. After excluding missing values for the main variables used (i.e., variables used in Eqs. (1) and (2)), we obtain a sample of 95,436 bank-quarters from 2014 to 2021, with the years 2015 and 2017 excluded due to missing YCOM survey results for these two years.

4.2. Descriptive statistics and correlations

Table 1 presents descriptive statistics of the regression variables for the full sample. As reported in Table 1, the mean (median) of $CBA_{i,t\text{-}1}$ is 0.18 (0.09), with a standard deviation of 2.08. The mean (median) of $CBA\_ALT_{i,t\text{-}1}$ is 0.74 (0.45) with a standard deviation of 3.92. The mean (median) of $NELPR_{i,t\text{-}1}$ is -2.57 (-2.50) with a standard deviation of 0.62. The mean (median) of $ZSCORE_{i,t\text{-}1}$ is -5.08 (-5.17) with a standard deviation of 0.80. The mean (median) of $CRISK_{i,t\text{-}1}$ is 5.33 (5.00) with a standard deviation of 2.95, suggesting that, on average, FEMA declared 5.33 major disasters for each county-quarter over a 15-year span. Table 2 presents the pairwise correlations across the regression variables for the full sample—as expected, $CBA_{i,t\text{-}1}$ is positively and significantly associated with $LLP_{i,t}$, providing some preliminary (univariate) support for a positive relationship between *CBA* and loan loss provisioning. Since these are pairwise univariate correlations, we rely on the multivariate analyses in the next section for formal inferences.

4.3. Empirical results

4.3.1. Main analysis

In this section, we report the results of the test of H1. Table 2 reports the results using $LLP_{i,t}$ as the dependent variable. In Column 1, we report the results of regressing $LLP_{i,t}$ on lagged climate risk ($CRISK_{i,t\text{-}1}$) and baseline control variables. We find a positive and significant relationship between lagged climate risk and LLP, indicating that climate risk alone is associated with more conservative loan loss provisioning behavior by banks, consistent with results documented in Dal Maso et al. (2024). In Column 2, we report results of regressing $LLP_{i,t}$ on $CBA_{i,t\text{-}1}$ with basic control variables. In Column 3, we report the results including both the basic control variables and additional macro and demographic control variables. In Column 4, we report results of regressing the one-year change in LLP ($\Delta LLP_{t/t\text{-}4}$) on the change of CBA from the previous survey to the current survey ($\Delta CBA_{s/s\text{-}1}$). In Columns 1 to 3, we include county, year, and quarter fixed effects, and in Column 4, we include county and quarter (i.e., only seasonality is controlled) fixed effects as the differencing of dependent and key explanatory variables already removes common annual shocks. Throughout Columns 2 to 4, we find positive and significant relationships between LLP and lagged CBA. The relation between LLP and lagged CBA is also economically significant. Using column 2 as an illustration, a one-standard-deviation increase in $CBA_{i,t\text{-}1}$ is associated with a 14.92% increase in LLP_t.[16] Overall, the results reported in Table 2 indicate that CBA plays an economically significant role in enhancing conservative loan loss accounting.

The signs of the coefficients of the control variables are generally consistent with prior literature. For example, consistent with prior studies such as Kanagaretnam et al. (2005) and Jin et al. (2021), we find that bank size is negatively associated with conservative loan loss accounting, suggesting that the extent of information asymmetry is less for larger banks, hence requiring less need for private information communication via loan loss accounting. We also find that earnings before tax and provisions are positively related to conservative loan loss accounting, consistent with income smoothing incentives with loan loss provisions (e.g., Kanagaretnam et al., 2004; Liu and Ryan, 2006; Bushman and Williams, 2012). Notably, we document a positive relationship between LLP and lagged Tier 1 Ratio, implying that better-capitalized banks tend to be more willing and able to recognize more expected credit losses.

Table 3 presents the regression results using loan loss allowances (ALL) as the dependent variable. In Column 1, we regress $ALL_{i,t}$ on lagged climate risk ($CRISK_{i,t\text{-}1}$) with county, year, and quarter fixed effects. We find a positive and significant relationship between lagged climate risk and ALL, indicating that banks in counties more exposed to climate risk hold higher general loan loss allowances. In Column 2, we report the results of regressing $ALL_{i,t}$ on $CBA_{i,t\text{-}1}$ with standard controls. Column 3 adds additional macroeconomic and demographic controls. Column 4 reports a specification using the 1-year change in ALL ($\Delta ALL_{t/t-4}$) as the dependent variable and the change in CBA from the previous to the current survey ($\Delta CBA_{s/s-1}$) as the main explanatory variable. In Columns 1 to 3, we include county, year, and quarter fixed effects, and in Column 4, we include county and quarter (i.e., only seasonality is controlled) fixed effects as the differencing of dependent

[13] The 14 loan categories include construction loans, farmland real estate loans, 1-4 family residential real estate loans, multifamily real estate loans, nonfarm nonresidential real estate loans, real estate loans in foreign offices, loans to depository institutions, agricultural production loans, commercial and industrial loans, credit cards, consumer loans other than credit cards, loans to foreign governments and institutions, lease financing receivables, and all other loans.

[14] In untabulated tests, we also test the empirical results with *ZSORE* and σNIM measured in eight-quarter windows. We obtain similar results.

[15] See Appendix A for a detailed description of these data sources.

[16] In Column 2, the impact of a one standard deviation increase in $CBA_{i,t\text{-}1}$ on $LLP_{i,t}$ is computed as 0.043 (the coefficient of $CBA_{i,t\text{-}1}$) $\times$ 2.0812 (the sample standard deviation of $CBA_{i,t\text{-}1}$) $\div$ (0.0006 $\times$ 1000) (the sample mean of $LLP_{i,t} \times$ 1000, because LLP is scaled by 1,000 in all displayed regressions) $\times$ 100% = 14.92%.

Table 1
Descriptive statistics and correlations.

Panel A: Descriptive Statistics

Variable	N	Mean	p25	p50	p75	SD
$CBA_{i,t-1}$	95,436	0.1841	-0.8570	0.0883	1.7984	2.0812
$CBA\_ALT_{i,t-1}$	95,436	0.7370	-1.2101	0.4511	3.7156	3.9238
$CBA\_WTD_{i,t-1}$	95,436	0.3427	-0.9989	0.0366	1.4290	1.8384
$\Delta CBA_{i,s/s-1}$	95,436	0.5368	-0.2404	0.5862	1.0702	0.8433
$CRISK_{i,t-1}$	95,436	5.3298	3.0000	5.0000	7.0000	2.9511
$LLP_{i,t}$	95,436	0.0006	0.0000	0.0002	0.0006	0.0016
$NELPR_{i,t}$	95,436	-2.5661	-2.8336	-2.5003	-2.2229	0.6268
$ZSCORE_{i,t}$	95,436	-5.0836	-5.6152	-5.1715	-4.6618	0.8022
$\sigma NIM_{i,t}$	95,436	0.0006	0.0003	0.0004	0.0006	0.0013
$ALL_{i,t}$	95,436	0.0149	0.0101	0.0128	0.0163	0.1928
$NPL_{i,t}$	95,436	0.0113	0.0019	0.0063	0.0142	0.0158
$NCO_{i,t}$	95,436	0.0004	0.0000	0.0000	0.0003	0.0015
$\Delta NPL_{i,t}$	95,436	-0.0003	-0.0014	-0.0001	0.0007	0.0091
$\Delta LOAN\%_{i,t}$	95,436	0.0176	-0.0101	0.0112	0.0354	0.0608
$EBTLLP_{i,t}$	95,436	0.0053	0.0033	0.0051	0.0069	0.0044
$TIER_{i,t-1}$	95,436	0.1266	0.1531	0.1266	0.1996	0.2135
$SIZE_{i,t-1}$	95,436	12.4860	11.5176	12.3002	13.2124	1.4826
$RESRELNS_{i,t}$	95,436	0.3312	0.1770	0.2949	0.4412	0.2201
$FMRELNS_{i,t}$	95,436	0.0815	0.0011	0.0305	0.1286	0.1062
$AGLNS_{i,t}$	95,436	0.0712	0.0000	0.0091	0.0883	0.1208
$CILNS_{i,t}$	95,436	0.1506	0.0687	0.1189	0.1892	0.1358
$CSLNS_{i,t}$	95,436	0.0531	0.0105	0.0287	0.0647	0.0741
$EDU_{i,t}$	95,436	0.0882	0.0003	0.0013	0.1715	0.1391
$MARITAL_{i,t}$	95,436	0.5016	0.4600	0.5070	0.5510	0.0703
$\Delta GDP_{i,t}$	95,436	0.0037	-0.0953	0.0000	0.0000	0.0263
$\Delta UNEMP_{i,t}$	95,436	-0.0554	-2.1000	0.0000	0.0000	0.7889

Panel B: Correlations among Selected Variables

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1)	$\boldsymbol{CBA_{i,t-1}}$	1.000												
(2)	$\boldsymbol{CBA\_ALT_{i,t-1}}$	0.961	1.000											
(3)	$\boldsymbol{CRISK_{i,t-1}}$	-0.053	-0.066	1.000										
(4)	$\boldsymbol{LLP_{i,t}}$	**0.022**	**0.022**	0.002	1.000									
(5)	$\boldsymbol{NELPR_{i,t}}$	0.176	0.211	0.016	0.110	1.000								
(6)	$\boldsymbol{ZSCORE_{i,t}}$	-0.249	-0.261	-0.023	0.038	-0.211	1.000							
(7)	$\boldsymbol{\sigma NIM_{i,t}}$	-0.152	-0.179	0.004	0.046	0.134	0.096	1.000						
(8)	$\boldsymbol{ALL_{i,t}}$	0.003	0.003	-0.004	0.058	-0.034	0.094	0.046	1.000					
(9)	$\boldsymbol{\Delta LOAN\%_{i,t}}$	0.057	0.069	0.011	0.077	-0.007	-0.010	-0.058	0.024	1.000				
(10)	$\boldsymbol{TIER1_{i,t-1}}$	0.083	0.094	-0.005	0.075	-0.572	0.140	-0.319	0.067	0.199	1.000			
(11)	$\boldsymbol{SIZE_{i,t-1}}$	0.332	0.338	0.009	0.052	0.282	-0.843	-0.079	-0.010	-0.007	-0.259	1.000		
(12)	$\boldsymbol{\Delta GDP_{i,t}}$	0.059	0.058	-0.002	-0.029	-0.013	0.001	0.001	0.001	-0.016	0.000	0.014	1.000	
(13)	$\boldsymbol{\Delta UNEMP_{i,t}}$	-0.013	-0.015	-0.006	0.063	0.041	0.013	0.026	-0.001	0.019	-0.001	-0.007	-0.282	1.000

This table provides the descriptive statistics of main variables. Variable definitions are provided in Appendix A. Continuous variables winsorized at 1%.
This table provides the Pearson correlations of the main variables used in this study. The detailed definitions of the variables are provided in Appendix A. All correlations with absolute values greater than 0.02 are statistically significant at the 0.01 level or better (two-tailed).

and key explanatory variables already removes common annual shocks. Throughout Columns 2 to 4, we find positive and significant relationships between ALL and lagged CBA. The relation between LLP and lagged CBA is also economically significant. Using Column 2 as an illustration, a one-standard-deviation increase in $CBA_{i,t-1}$ is associated with a 1.54% increase *in* ALL_t.[17] Overall, the results reported in Table 3 suggest that CBA plays a significant role in enhancing conservative loan loss accounting.

4.3.2. *The confounding factor of climate risk*

However, a key concern with our main specification is the potential difficulty in disentangling anticipated climate risk from banks' subjective beliefs or attitudes toward climate risk. For instance, banks located in regions recently affected by climate-related disasters may adjust their behavior in response to physical climate risks, such as disaster risks, by increasing liquidity buffers (e.g., holding higher cash reserves) or risk management practices (e.g., increasing loan loss reserves). To address this concern, we employ two main strategies to demonstrate that the relationship between CBA and conservative loan loss accounting persists even after accounting for regional climate risk levels.

4.3.2.1. Univariate analysis. In the first strategy, we perform univariate comparisons of abnormal LLP and ALL between high- and low-CBA counties within subsamples split by climate risk exposure. Specifically, we compare the mean levels of abnormal LLP (*ABLLP*) and abnormal ALL (*ABALL*) across counties in the top versus bottom quartile of CBA, separately for counties in the top and bottom quartiles of lagged climate risk. *ABLLP* and *ABALL* are two common proxies used by prior studies for conservative loan loss accounting.

We measure *ABLLP* by first estimating an LLP model following Kanagaretnam (2010) and Basu et al. (2020) as follows:

$$\begin{aligned} LLP_{i,t} = {} & \alpha_0 + \alpha_1 ALL_{i,t-1} + \alpha_2 NPL_{i,t-1} + \alpha_3 LOANS_{i,t} + \alpha_4 \Delta LOAN\%_{i,t} \\ & + \alpha_5 NCO_{i,t} + \ \alpha_6 \Delta NPL_{i,t} \times \ D\Delta NPL_{i,t} + \alpha_6 \Delta NPL_{i,t} + \alpha_6 D\Delta NPL_{i,t} \\ & + \alpha_7 \Delta GDP_{i,t} + \alpha_8 \Delta UNEMP_{i,t} + \ Bank\ FE + Quarter\ FE + \varepsilon_t \end{aligned} \tag{3}$$

Where *Bank FE* and *Quarter FE* represent bank and year-quarter fixed effects. All other variables are defined in the same way as in Eqs. (1) and (2). The residual captures a bank's deviation from the normal, or

[17] In Column 2, the impact of a one standard deviation increase in $CBA_{i,t-1}$ on $ALL_{i,t}$ is computed as 0.110 (the coefficient of $CBA_{i,t-1}$) × 2.0812 (the sample standard deviation of $CBA_{i,t-1}$) ÷ (0.0149 × 1000) (the sample mean of $ALL_{i,t}$ × 1000, because ALL is scaled by 1,000 in all displayed regressions) × 100% = 1.54%.

Table 2
CBA and loan loss provisions.

	(1) LLP_t		(2) LLP_t		(3) LLP_t		(4) $\Delta LLP_{t/t-4}$	
			Baseline Model		More Controls		Regression with Differences	
CBA_{t-1}			**0.043*** **	**(3.85)**	**0.044*** **	**(4.13)**		
$\Delta CBA_{s/s-1}$							**0.164*** **	**(5.18)**
$CRISK_{t-1}$	0.034***	(8.04)	-0.008	(-1.46)	-0.007	(-1.35)	-0.042**	(-2.38)
$SIZE_{t-1}$	0.012	(1.22)	-0.027**	(-2.36)	-0.027**	(-2.36)	0.026	(0.99)
ALL_{t-1}	-22.272***	(-11.80)	-5.982**	(-2.25)	-6.001**	(-2.26)	-74.865***	(-7.73)
NPL_{t-1}	10.618***	(20.53)	4.552***	(5.57)	4.572***	(5.58)	-1.828	(-0.88)
ΔNPL_t	22.030***	(8.44)	16.991***	(4.95)	16.963***	(4.94)	28.060***	(3.69)
$D\Delta NPL_t$	-0.145***	(-8.59)	-0.060***	(-3.14)	-0.059***	(-3.12)	-0.033	(-0.83)
$D\Delta NPL_t \times \Delta NPL_t$	-11.252***	(-5.03)	-8.918**	(-2.13)	-8.857**	(-2.12)	-51.540***	(-3.65)
$LOANS_t$	0.655***	(9.54)	0.635***	(7.63)	0.632***	(7.60)	0.045	(0.12)
$\Delta LOANS_t$	2.349***	(14.76)	2.519***	(11.47)	2.523***	(11.50)	0.108	(0.06)
$EBTLLP_t$	19.903***	(6.73)	28.082***	(7.25)	28.144***	(7.28)	13.216	(0.76)
NCO_t	634.218***	(89.77)	604.110***	(36.98)	604.045***	(36.98)	486.657***	(5.79)
$TIER1_{t-1}$	0.322*	(1.84)	0.642***	(2.68)	0.638***	(2.67)	0.633	(0.73)
$CILNS_t$	0.305**	(2.40)	0.557***	(3.67)	0.553***	(3.65)	0.677	(0.79)
$CSLNS_t$	1.292***	(5.91)	1.965***	(7.60)	1.964***	(7.60)	-1.949**	(-2.11)
$RESRELNS_t$	-0.551***	(-10.15)	-0.357***	(-5.54)	-0.358***	(-5.56)	0.075	(0.30)
$FMRELNS_t$	-0.426***	(-4.93)	-0.324***	(-3.14)	-0.324***	(-3.18)	-0.165	(-0.73)
$AGLNS_t$	-0.505***	(-6.06)	-0.276***	(-2.68)	-0.284***	(-2.76)	0.492	(1.22)
$\Delta GDPt$	-0.228**	(-2.02)	0.078	(0.46)	0.032	(0.20)	-0.410	(-0.98)
$\Delta UNEMP_t$	0.003	(0.49)	0.035***	(4.05)	0.035***	(4.01)	0.009	(0.57)
GDP_{t-1}					-0.050	(-0.64)	0.031	(0.25)
EDU_{t-1}					-0.000***	(-3.27)	-0.000	(-1.20)
$MARITAL_{t-1}$					0.356	(1.07)	0.654	(0.59)
Constant	0.218	(0.83)	0.271	(0.93)	-0.294	(-0.67)	-0.452	(-0.68)
County FE	Yes		Yes		Yes		Yes	
Year FE	Yes		Yes		Yes		No	
Quarter FE	Yes		Yes		Yes		Yes	
Adj. R-squared	0.45		0.49		0.49		0.06	
N	259,915		95,436		95,436		85,447	

This table reports the relation between loan loss provisions and CBA. Column 1 uses LLP_t as the dependent variable and $CRISK_{t-1}$ as the main explanatory variable. Column 2 uses LLP_t as the dependent variable and CBA_{t-1} as the main explanatory variable. Column 3 uses LLP_t as the dependent variable and CBA_{t-1} as the main explanatory variable, with additional county-level control variables (i.e., GDP_{t-1}, EDU_{t-1}, and $MARITAL_{t-1}$). Column 4 uses 1-year changes of LLP ($\Delta LLP_{t/t-4}$) as the dependent variable and changes in CBA derived from the previous survey results to the CBA derived from current survey results ($\Delta CBA_{s/s-1}$) as the main explanatory variable. Columns 1, 2, and 3 include county, year, and quarter fixed effects. Column 4 includes county and quarter (seasonality) fixed effects (year fixed effects are not included as first-differencing already removes common annual shocks). Robust standard errors are clustered on banks. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively, based on a two-tailed test. T-statistics are reported in parentheses. Continuous variables are winsorized at the 1% level. LLP_t (in regression) is scaled by multiplying 1,000 for display purposes. Subscript *i* is omitted to conserve space.

nondiscretionary, level of LLP (denoted as *ABLLP*).

Next, we follow Beck and Narayanamoorthy (2013) and Jin et al. (2018), and estimate the following model to construct the proxy for ABALL:

$$\begin{aligned} ALL_{i,t} = {} & \beta_0 + \beta_1 AVENCO_{i,t} + \beta_2 NPL_{i,t} + \beta_3 NPL_{i,t-1} + \beta_4 RESRELNS_{i,t} \\ & + \beta_5 FMRELNS_{i,t} + \beta_6 AGLNS_{i,t} + \beta_7 CILNS_{i,t} + \beta_8 CSLNS_{i,t} \\ & + \beta_9 SIZE_{i,t-1} + \beta_{10} T1R_{i,t-1} + \beta_{11} \Delta LOAN\%_{i,t} + \beta_{12} EBTLLP_{i,t} \\ & + \beta_{13} \Delta GDP_{i,t} + \beta_{14} \Delta UNEMP_{i,t} + Bank\ FE + Quarter\ FE + \varepsilon \end{aligned} \quad (4)$$

Where all variables are defined in the same way as in Eqs. (1) and (2). The residual captures a bank's deviation from the normal, or nondiscretionary, level of ALL (denoted as *ABALL*).

As reported in Panel A of Table 4, counties with high CBA scores consistently exhibit higher abnormal ALL than those with low CBA scores. This pattern holds in both high climate risk regions (mean difference = 0.0893, t = 9.22) and low climate risk regions (mean difference = 0.0216, t = 1.97). Similarly, Panel B shows that abnormal LLP is significantly higher in high-CBA counties in both high climate risk regions (difference = 0.0676, t = 7.11) and low climate risk regions (difference = 0.0359, t = 3.72). These results demonstrate that the positive relationship between CBA and conservative loan loss behavior holds even when variation in regional climate risk is limited. The persistence of this association across both high and low climate risk areas suggests that the relationship is not entirely attributable to physical climate exposure, and that CBA could independently contribute to banks' loan loss provisioning practices.

4.3.2.2. Adjusted climate beliefs and attitudes: two-stage approach. In Table 5, we implement a two-stage regression strategy to further address potential confounding by climate risk and other county-level factors. In the first stage (Column 1), we regress CBA on lagged climate risk and a set of county-level controls, including education, marital status, GDP per capita, unemployment, and the share of population over 18. This regression yields a high adjusted R-squared of 0.97, indicating that much of the variation in CBA is explained by these lagged observable characteristics.

We then extract the residual from this regression—i.e., the component of CBA not explained by regional climate risk and several other county-level factors—and use it in second-stage regressions of LLP and ALL. In Column 2, we find that the residual ($ADJ\_CBA_{i,t-1}$) remains positively associated with LLP (coefficient = 0.0355; t = 3.07). In Column 3, we observe a similar result for ALL (coefficient = 0.1264; t = 2.76). These coefficients are statistically significant at the 1% level and robust to a full set of control variables and county, year, and quarter fixed effects.

4.3.2.3. Subsample analysis by climate risk level. To further assess whether the relationship between CBA and conservative loan loss accounting varies with climate risk exposure, we estimate baseline regressions of LLP and ALL on CBA separately for low and high climate risk subsamples, as reported in Table 6. In both subsamples, $CBA_{i,t-1}$ is positively and significantly associated with LLP and ALL. The magnitude

Table 3
CBA and loan loss allowances.

	(1) ALL_t		(2) ALL_t Baseline Model		(3) ALL_t More Controls		(4) $\Delta ALL_{t/t-4}$ Regression with Differences	
CBA_{t-1}			**0.110****	**(2.40)**	**0.107****	**(2.33)**		
$\Delta CBA_{s/s-1}$							**0.207*****	**(5.10)**
$CRISK_{t-1}$	0.042***	(2.96)	-0.031**	(-1.99)	-0.030*	(-1.93)	0.001	(0.03)
$AVENCO_t$	-21.447	-21.447	309.4**	(2.26)	309.2**	(2.25)	-582.4***	(-5.46)
NPL_t	115.791***	115.791***	75.595***	(11.50)	75.569***	(11.50)	51.165***	(8.62)
NPL_{t-1}	-70.330***	-70.330***	-75.235***	(-10.69)	-75.143***	(-10.67)	-35.257***	(-5.41)
$SIZE_{t-1}$	-0.015	-0.015	-0.252***	(-3.06)	-0.253***	(-3.06)	-0.003	(-0.07)
$TIER1_{t-1}$	7.954	1.29	6.029**	(2.05)	6.027**	(2.05)	-1.314	(-1.49)
$LOANS_t$	-3.455	-3.455	-0.657	(-0.97)	-0.661	(-0.97)	2.323***	(5.80)
$\Delta LOANS_t$	10.961**	10.961**	4.581***	(3.59)	4.592***	(3.60)	-3.709**	(-2.17)
ALL_{t-1}	1076.4***	1076.4***	1055.7***	(45.57)	1055.7***	(45.55)	61.454***	(5.30)
$EBTLLP_t$	116.011**	116.011**	59.393*	(1.94)	59.397*	(1.94)	84.975***	(4.26)
$CILNS_t$	-0.489	-0.489	-0.121	(-0.35)	-0.122	(-0.35)	1.223***	(3.77)
$CSLNS_t$	0.783	0.783	0.467	(1.08)	0.474	(1.11)	-0.141	(-0.29)
$RESRELNS_t$	-2.674**	-2.674**	-1.029**	(-2.04)	-1.042**	(-2.07)	2.658***	(4.52)
$FMRELNS_t$	0.731	0.731	0.543	(0.34)	0.538	(0.34)	3.021***	(3.43)
$AGLNS_t$	2.697	2.697	3.319*	(1.81)	3.317*	(1.80)	3.459***	(3.78)
ΔGDP_t	0.213	0.213	0.106	(0.20)	0.212	(0.43)	-0.309	(-0.48)
$\Delta UNEMP_t$	0.115**	0.115**	0.107***	(2.83)	0.103***	(2.77)	0.053**	(2.20)
GDP_{t-1}					0.055	(0.20)	0.550**	(2.24)
EDU_t					-0.000***	(-2.89)	-0.000***	(-3.41)
$MARITAL_t$					1.276	(1.11)	-2.502	(-1.21)
Constant	-0.060	(-0.05)	2.205**	(2.07)	0.712	(0.17)	-15.973***	(-4.03)
County FE	Yes		Yes		Yes		Yes	
Year FE	Yes		Yes		Yes		No	
Quarter FE	Yes		Yes		Yes		Yes	
Adj. R-squared	0.48		0.84		0.84		0.09	
N	259,915		95,436		95,436		85,447	

This table reports the relation between loan loss allowances and CBA. Column 1 uses ALL_t as the dependent variable and $CRISK_{t-1}$ as the main explanatory variable. Column 2 uses ALL_t as the dependent variable and CBA_{t-1} as the main explanatory variable. Column 3 uses ALL_t as the dependent variable and CBA_{t-1} as the main explanatory variable, with additional county-level control variables (i.e., GDP_{t-1}, EDU_{t-1}, and $MARITAL_{t-1}$). Column 4 uses 1-year changes of ALL ($\Delta ALL_{t/t-4}$) as the dependent variable and changes in CBA derived from the previous survey results to the CBA derived from current survey results ($\Delta CBA_{s/s-1}$) as the main explanatory variable. Columns 1, 2, and 3 include county, year, and quarter fixed effects. Column 4 includes county and quarter (seasonality) fixed effects (year fixed effects are not included as first-differencing already removes common annual shocks). Robust standard errors are clustered on banks. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively, based on a two-tailed test. T-statistics are reported in parentheses. Continuous variables are winsorized at the 1% level. ALL_t (in regression) are scaled by multiplying 1,000 for display purposes. Subscript *i* is omitted to conserve space.

of the coefficients is comparable across subsamples, indicating that the influence of CBA on conservative loan loss behavior is not confined to high climate risk areas. While climate risk may shape banks' provisioning behavior more broadly, these results suggest that the effect of CBA persists even when variation in climate risk is limited.

Taken together, the results from Tables 4–6 provide consistent evidence supporting the robustness of our main findings. The univariate analysis in Table 4 shows that abnormal provisioning is higher in high-CBA counties regardless of the level of regional climate risk. The two-stage residual analysis in Table 5 further demonstrates that the component of CBA orthogonal to climate risk and other demographic factors remains a significant predictor of conservative loan loss behavior. Table 6 adds to this evidence by showing that the baseline association between CBA and provisioning holds across both low and high climate risk subsamples, with similar effect sizes. These results reinforce the interpretation that CBA captures a distinct and meaningful influence on banks' provisioning behavior, above and beyond the effects of regional climate conditions.

4.3.3. Additional robustness tests

4.3.3.1. Reverse causality minimization. To address concerns that the documented relationship between CBA and conservative loan loss accounting may reflect reverse causality—i.e., prior provisioning behavior may influence the CBA—we implement a reverse causality minimization approach following Godfrey et al. (2024).

As shown in Table 7, we first regress CBA_t on lagged loan loss provisions (LLP_{t-1}) and a set of lagged county-level controls—including education, marital status, GDP per capita, GDP growth, and unemployment—to obtain the fitted and residual components of CBA. The fitted values capture variation in CBA potentially driven by prior provisioning or local socioeconomic characteristics, while the residual reflects the portion of CBA orthogonal to these factors.

We then re-estimate our main regressions of LLP and ALL using both the fitted and residualized CBA components as explanatory variables. Results reported in Columns 2 and 3 of Table 7 show that the residualized CBA ($RESID\_CBA_{i,t-1}$) remains positive and statistically significant in both models after controlling for a full set of bank-level, macroeconomic, and demographic controls and including county and year-quarter fixed effects. These findings indicate that the portion of CBA unrelated to past LLP continues to explain variation in loan loss provisioning, mitigating concerns that our results are driven by reverse causality.

4.3.3.2. Oster (2019) test. To further assess the robustness of our findings to potential omitted variable bias, we implement the method proposed by Oster (2019). This approach compares coefficient stability and changes in model fit (R-squared) between a baseline regression (with limited controls) and a fully saturated model (with the full set of firm- and county-level controls) and estimates the implied Delta (δ)—the degree of selection on unobservables relative to observables required to eliminate the main result.

Table 8 Panel A reports the full Oster (2019) test results for our baseline specifications. Using LLP as the dependent variable (Columns 1 and 2), the estimated δ is 9.30. Using ALL as the dependent variable (Columns 3 and 4), the δ is 5.83. These values imply that omitted

Table 4
CBA and conservative loan loss accounting
– Univariate analysis incorporating climate risk.

Panel A: Abnormal Allowances for Loan Losses in High vs. Low CBA Counties for Subsamples of High Climate Risk and Low Climate Risk Counties

Variable of interest = Abnormal ALL (ABALL)		(1)	(2)	(3)
		High CBA	Low CBA	**Diff: (1) – (2)**
(1)	High Climate Risk	0.0483 (N = 6,426)	-0.0409 (N = 6,772)	**0.0893*** (9.22)**
(2)	Low Climate Risk	0.0368 (N = 6,332)	0.0151 (N = 7,160)	**0.0216** (1.97)**

Panel B: Abnormal Bank Loan Loss Provisions in High vs. Low CBA Counties for Subsamples of High Climate Risk and Low Climate Risk Counties

Variable of interest = Abnormal LLP (ABLLP)		(1)	(2)	(3)
		High CBA	Low CBA	**Diff: (1) – (2)**
(1)	High Climate Risk	0.0654 (N = 6,515)	-0.0023 (N = 6,785)	**0.0676*** (7.11)**
(2)	Low Climate Risk	0.0094 (N = 6,660)	-0.0265 (N = 7,177)	**0.0359*** (3.72)**

This table compares the differences in the mean values of *ABALL* between county-years with the highest quartile of CBA_{t-1} (Column 1) and county-years with the lowest quartile of CBA_{t-1} (Column 2), for county-years with the highest quartile of climate risk (Row 1) and county-years with the lowest quartile of climate risk (Row 2). Climate risk is measured by $CRISK_{t-1}$. T-statistics are reported in parentheses. Continuous variables are winsorized at the 1% level.
This table compares the differences in the mean values of ABLLP between county-years with the highest quartile of CBA_{t-1} (Column 1) and county-years with the lowest quartile of CBA_{t-1} (Column 2), for county-years with the highest quartile of climate risk (Row 1) and county-years with the lowest quartile of climate risk (Row 2). Climate risk is measured by $CRISK_{t-1}$. T-statistics are reported in parentheses. Continuous variables are winsorized at the 1% level.

variables would need to be approximately 9 and 6 times more influential, respectively, than the included variables in the current model to fully eliminate the estimated effect of CBA on conservative loan loss accounting. These large δ values provide evidence against omitted variable bias being a plausible explanation for our baseline results.

Table 8 Panel B reports Oster (2019) Delta values for all main regressions in a single consolidated view (following Hoepner et al., 2025). This table summarizes coefficient estimates and corresponding Oster δ across key specifications. While δ values vary across specifications and are lower in some subsamples, the majority indicate that unobserved confounders would need to be substantially stronger than observed controls to overturn our findings.

4.3.3.3. Subsample tests and alternative measures. Table 9 Panel A presents additional robustness tests examining whether the relationship between CBA and conservative loan loss accounting holds when restricting the sample to banks with greater geographic concentration. Columns 1 and 2 limit the sample to banks whose branch deposits are entirely located within a single county (100% concentration), while Columns 3 and 4 use a 90% threshold. Across all specifications, we find that *CBA* remains significantly and positively associated with both *LLP* and *ALL*, with economically meaningful magnitudes. This evidence suggests that our results are not driven by biased geographic matching.

Table 9 Panel B explores whether the relationship between CBA and conservative loan loss accounting differs before and after the onset of the COVID-19 pandemic. Columns 1 and 2 restrict the sample to post-2020 observations, while Columns 3 and 4 use pre-2020 data. Across both periods, *CBA* remains significantly positively associated with *LLP* and *ALL*, with larger magnitudes and stronger significance in the pre-COVID sample. These results suggest that the documented association between CBA and conservative provisioning is not confined to a specific time window and remains robust to potential economical and social changes around the pandemic.

Table 9 Panel C examines the robustness of our findings using two alternative measures of climate beliefs and attitudes: *CBA_ALT* and *CBA_WTD*. Columns 1 and 2 use *CBA_ALT*, derived as the first principal component from a factor analysis of 12 YCOM variables, while Columns 3 and 4 use *CBA_WTD*, which aggregates *CBA* across counties weighted by banks' branch-level deposit exposure. Across both measures, we continue to find a positive and statistically significant relationship between *CBA* and both *LLP* and *ALL*.

Table 9 Panel D tests the robustness of our baseline results using three alternative measures of climate risk. Columns 1 and 2 use *CDD* as the alternative measure of climate risk, defined as total county-wide climate-related property damage (in millions of USD) from 2010–2017. Columns 3 and 4 use *CRISK_5YRS*, which counts FEMA-declared major disasters in a five-year window (instead of a 15-year window), and Columns 5 and 6 use *CRISK_RARE*, which tracks rare FEMA-declared disasters over a fifteen-year span. Across all specifications, the coefficient on *CBA* remains positive and statistically significant, indicating that our baseline results are not sensitive to how climate risk is measured.

4.3.4. CBA and bank risk-taking

We report the results of our tests of H2, which hypothesizes that CBA is negatively related to both bank loan portfolio risk-taking and overall bank risk-taking. As introduced in Section 3.4, we measure bank loan portfolio risk-taking with *NELPR* and measure overall bank risk-taking with *ZSCORE* and *σNIM*. In Table 10 Column 1, we regress $NELPR_{i,t}$ on $CBA_{i,t-1}$ with control variables including the climate risk ($CRISK_{t-1}$), bank-level controls, macro-level controls, and bank fixed effects. We find that $CBA_{i,t-1}$ is negatively and significantly associated with $NELPR_{i,t}$. This result suggests that *CBA* has a first-order effect on banks' loan portfolio risk-taking. In Table 10, columns 2 and 3, we report the results with $ZSCORE_{t/t-3}$ and $\sigma NIM_{t/t-3}$ as dependent variables, and we find that CBA is negatively and significantly associated with both measures of bank overall risk-taking. This result indicates that CBA has a first-order effect on banks' overall risk-taking. In addition, we also report the coefficients and t-stats for all three regressions with standardized variables: we find that across the three regressions, CBA remains negatively and significantly associated with the three measures of bank risk-taking. The relation between CBA and bank risk-taking is also economically significant. Using standardized variables regressions as examples, a one-standard-deviation increase in lagged CBA is associated with a 1.07%, 0.57%, and 3.47% decrease in *NELPR, ZSCORE*, and *σNIM*.[18] Overall, the results reported in Table 10 indicate that CBA plays an economically significant role in mitigating bank risk-taking.

4.3.5. The effect of CBA on the sensitivity of bank risk to climate Risk

We further investigate the potential consequences of the positive relationship between CBA and conservative loan loss accounting, namely, the decrease in the sensitivity of bank risk to climate risk. We conduct such consequence analyses to support our main argument that CBA influences bank loan accounting through enhanced climate-related credit risk management. As discussed in H3, we expect a positive moderating effect of CBA on the relationship between bank risk and climate risk.

As explained in Section 3.2, we use *CRISK* as the proxy for climate

[18] We convert these effects into percentage terms by multiplying the standardized coefficient by the standard deviation of the dependent variable and scaling the resulting change by the mean of the dependent variable. For example, the impact of a one standard deviation increase in $CBA_{i,t-1}$ on $NELPR_{i,t}$ is computed as -0.044 (the standardized coefficient of $CBA_{i,t-1}$) × 0.6268 (the sample standard deviation of $NELPR_{i,t}$) ÷ 2.5661 (the absolute value of sample mean of $NELPR_{i,t}$) × 100% = -1.07%.

Table 5
Adjusted climate beliefs and attitudes: regression analysis incorporating climate risk.

	(1)			(2)		(3)	
	First Stage Regression		Second Stage Regressions				
	CBA_t			LLP_t		ALL_t	
$CRISK_{t-1}$	0.0049***	(4.08)	ADJ_CBA_{t-1}	0.0355***	(3.07)	0.1264***	(2.76)
EDU_{t-1}	0.0001***	(4.16)	$CRISK_{t-1}$	0.0008	(0.17)	-0.0296**	(-2.09)
$MARITAL_{t-1}$	1.2938***	(15.84)	$SIZE_{t-1}$	0.0030	(0.30)	-0.0225	(-0.38)
GDP_{t-1}	0.2583***	(18.26)	ALL_{t-1}	-6.9599**	(-2.53)		
$UNEMP_{t-1}$	0.0109***	(3.54)	NPL_{t-1}	4.5044***	(6.33)	-68.4776***	(-11.97)
$POP18_{t-1}$	-0.1168***	(-5.87)	NCO_t	608.3474***	(40.18)		
			ΔNPL_t	18.2837***	(6.09)		
			$D\Delta NPL_t$	-0.0477***	(-3.15)		
			$D\Delta NPL_t \times \Delta NPL_t$	-8.3935**	(-2.45)		
			$LOANS_t$	0.7500***	(8.35)	0.9032	(1.44)
			$\Delta LOANS_t$	2.2068***	(11.95)	3.9358***	(4.52)
			$EBTLLP_t$	26.5492***	(6.78)	37.7937	(1.08)
			$AVENCO_t$			233.3233**	(2.02)
			NPL_t			68.7505***	(12.89)
			$TIER1_{t-1}$	0.4757**	(2.26)	5.9478*	(1.91)
			$CILNS_t$	0.4968***	(3.22)	0.7983	(0.56)
			$CSLNS_t$	2.0465***	(8.04)	3.1665**	(1.99)
			$RESRELNS_t$	-0.3738***	(-5.43)	-0.6477	(-1.05)
			$FMRELNS_t$	-0.3079***	(-3.08)	0.7167*	(1.74)
			$AGLNS_t$	-0.2197**	(-2.31)	-1.1437**	(-2.11)
			$\Delta GDPt\text{-}1$	0.0367	(0.29)	0.1232	(0.34)
			$\Delta UNEMP_{t-1}$	0.0738***	(6.54)	0.1080***	(3.24)
			GDP_{t-1}	-0.0300	(-0.48)	0.2766	(1.20)
			EDU_t	-0.0000***	(-3.67)	-0.0000***	(-2.63)
			$MARITAL_t$	0.3857	(1.27)	2.3635**	(2.16)
Constant	-2.9489***	(-21.55)	*Constant*	-0.1967	(-0.21)	-7.7191*	(-1.94)
County-Quarter FE	Yes		County-Quarter FE	Yes		Yes	
Adj. R-squared	0.97		Adj. R-squared	0.50		0.85	
N	95,436		N	95,436		95,436	

This table reports the relation between adjusted CBA and LLP/ALL in two stages. In stage 1 (Column 1), *CBA* is regressed on *CRISK* and several county-level demographic and macroeconomic variables. The residual in stage 1 regression is denoted as adjusted CBA (*ADJ_CBA*). In Columns 2 and 3, LLP and ALL are regressed on ADJ_CBA_{t-1}. Columns 2 and 3 also include county, year, and quarter fixed effects. Robust standard errors are clustered on banks. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively, based on a two-tailed test. T-statistics are reported in parentheses. Continuous variables are winsorized at the 1% level. Dependent variables (in regression) are scaled by multiplying 1,000 for display purposes. Subscript *i* is omitted to conserve space.

risk. Moreover, we measure bank loan portfolio risk with *NELPR* and overall bank risk with *ZSCORE*. With these measurements, we estimate a negative moderating effect of CBA on the relationship between bank risk (proxied by *NELPR* and *ZSCORE*) and climate risk (*CRISK*). Because *CRISK* is also a continuous variable, we transform *CBA* into *CBA_MC*, which is a mean-centered version of *CBA*.

We report the results of the consequences test in Table 11. In Column 1, we regress bank loan portfolio risk-taking ($NELPR_{i,t}$) on lagged climate risk ($CRISK_{i,t-1}$) and a full list of bank-level and macro-level control variables. We find that, without incorporating the county-year level CBA, climate risk is positively associated with bank loan portfolio risk-taking. In Column 2, we regress $NELPR_{i,t}$ on $CBA\_MC_{i,t-1}$, $CRISK_{i,t-1}$, and the interaction of the two ($CBA\_MC_{i,t-1} \times NELPR_{i,t-1}$), and we find that the coefficient on $CBA\_MC_{i,t-1} \times NELPR_{i,t-1}$ is negative and significant, suggesting that in county-years with higher levels of CBA, the sensitivity of bank risk to climate risk is lower, consistent with H3. Moreover, we repeat the regressions in columns 1 and 2 by replacing $NELPR_{i,t}$ with $ZSCORE_{t/t-3}$, and we report the associated results in columns 3 and 4. We find consistent results. Overall, these consequence tests suggest that the sensitivity of bank risk to climate risk is attenuated by CBA, which supports our main argument that CBA influences conservative loan loss accounting through the enhancement of climate-related risk management, which reduces banks' climate risk exposure.

In addition, we repeat the CBA and bank risk-taking tests using the two alternative measures of CBA (i.e., *CBA_WTD, CBA_ALT*). We show the results with bank risk-taking proxied by $NELPR_{i,t}$ and $ZSCORE_{t/t-3}$. In all three columns of Table 12, we find that CBA is significantly negatively related to bank risk-taking.

5. Conclusion

Our study examines bank risk management through the influence of CBA on banks' conservative loan loss accounting practices, specifically focusing on allowance for loan losses (ALL) and loan loss provisions (LLP). We document a significant and positive relationship between CBA and ALL and LLP (i.e., conservative loan loss accounting). We argue that one primary channel through which CBA influences conservative loan loss accounting is enhanced climate-related credit risk management. We support this channel by documenting that CBA is negatively associated with both bank loan portfolio risk-taking and the overall level of bank risk-taking. In cross-sectional tests, we also find that the sensitivity of bank risk to climate risk is significantly less pronounced in counties with lower levels of CBA. Our paper bridges a tangible gap in the existing literature by exploring the impact of CBA on corporate behaviors, particularly in the banking sector.

Our research makes significant contributions to the existing literature in several ways. First, it extends the study of climate-change-related perceptions, beliefs, and attitudes by examining the impact of CBA on corporate behaviors and economic outcomes, particularly in the banking sector, which can be particularly sensitive to climate risks. We document CBA as a significant determinant of conservative bank loan loss provisioning and show that banks' susceptibility to climate risks is lower in counties with higher levels of CBA. In particular, our finding highlights that CBA is equally or more salient than climate risk itself in influencing banks' financial practices—it demonstrates that banks in higher CBA regions adopt more conservative loan loss accounting practices regardless of the actual level of climate risk exposure. Second, we build on research exploring factors influencing bank loan loss provisioning, identifying CBA as a novel influence. Finally, we contribute to bank

Table 6
Regression results in subsamples of counties with high and low climate risks.

Subsample	(1) Low Climate Risk (*CRISK_HIGH* = 0)		(2)		(3) High Climate Risk (*CRISK_HIGH* = 1)		(4)	
	LLP_t		ALL_t		LLP_t		ALL_t	
CBA_{t-1}	**0.038****	**(2.06)**	**0.174****	**(1.99)**	**0.031****	**(2.12)**	**0.191****	**(2.54)**
$SIZE_{t-1}$	-0.005	(-0.20)	-0.212	(-1.52)	0.010	(0.58)	-0.212	(-1.40)
ALL_{t-1}	7.923	(1.49)	1121.632***	(22.21)	-16.623***	(-3.57)	1011.423***	(27.57)
NPL_{t-1}	2.768	(1.63)	-95.193***	(-7.16)	6.850***	(4.29)	-63.784***	(-5.24)
ΔNPL_t	19.238**	(2.42)			19.836**	(2.39)		
$D\Delta NPL_t$	-0.077	(-1.51)			-0.057*	(-1.80)		
$D\Delta NPL_t \times \Delta NPL_t$	-15.352**	(-2.12)			-11.785	(-1.09)		
$LOANS_t$	0.885***	(5.50)	-1.422	(-0.77)	0.304*	(1.77)	-1.548	(-1.49)
$\Delta LOANS_t$	2.376***	(6.42)	8.732***	(2.83)	2.969***	(7.06)	1.447	(1.14)
$EBTLLP_t$	44.858***	(6.84)	53.626	(0.77)	8.857	(1.12)	80.590	(1.37)
NCO_t	604.535***	(19.61)			583.644***	(15.80)		
$AVENCO_t$			543.442**	(2.07)			-172.451***	(-3.09)
NPL_t			90.118***	(5.54)			72.985***	(5.69)
$TIER1_{t-1}$	0.443	(1.31)	10.082*	(1.81)	0.899**	(2.35)	2.951	(1.09)
$CILNS_t$	0.318	(1.13)	-3.499*	(-1.70)	1.265***	(3.61)	5.486	(1.56)
$CSLNS_t$	3.064***	(5.67)	11.057**	(2.37)	1.717**	(2.40)	-1.240	(-0.77)
$RESRELNS_t$	-0.363***	(-2.79)	-0.614	(-0.74)	-0.299*	(-1.89)	0.618	(1.08)
$FMRELNS_t$	-0.369	(-1.58)	1.021	(1.14)	-0.039	(-0.19)	1.266	(1.24)
$AGLNS_t$	-0.291	(-1.47)	-1.965	(-1.53)	-0.060	(-0.28)	-0.554	(-0.82)
ΔGDP_{t-1}	0.062	(0.17)	1.806	(1.50)	-0.012	(-0.03)	-0.734	(-0.65)
$\Delta UNEMP_{t-1}$	0.072***	(6.34)	0.144***	(2.70)	0.065***	(4.76)	0.172**	(2.53)
Constant	-1.129***	(-2.93)	1.391	(0.50)	-0.328	(-1.03)	2.137	(1.47)
Adj. R-squared	0.55		0.81		0.44		0.88	
County-Quarter FE	Yes		Yes		Yes		Yes	
N	27,436		27,436		22,194		22,194	

This table reports the relationship between LLP/ALL and CBA. Regressions are conducted on subsamples of banks based on the quartile of climate risks measured by CRISK. Columns 1 and 2 report results in the sample where *CRISK_HIGH = 0*. Columns 3 and 4 report results in the sample where *CRISK_HIGH = 1*. Robust standard errors are clustered at the bank level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests. T-statistics are reported in parentheses. All continuous variables are winsorized at the 1% level. Dependent variables are scaled by a factor of 1,000 for display purposes. Subscript *i* is omitted to conserve space.

Table 7
Reverse causality minimization.

	(1)			(2)		(3)	
Stage 1 – Decomposing fitted and residual CBA			Stage 2 – Regressing LLP on both fitted and residual CBA				
	CBA_t			LLP_t		ALL_t	
LLP_{t-1}	0.003***	(4.15)	$FITTED\_CBA_{t-1}$	0.071*	(1.94)	0.122	(0.94)
EDU_{t-1}	0.000***	(3.62)	**$RESID\_CBA_{t-1}$**	**0.037*** **	**(3.37)**	**0.097** **	**(2.20)**
$MARITAL_{t-1}$	0.697***	(7.62)	$CRISK_{t-1}$	-0.008	(-1.40)	-0.033**	(-2.05)
GDP_{t-1}	0.317***	(39.71)	$SIZE_{t-1}$	0.008	(0.79)	-0.010	(-0.18)
ΔGDP_{t-1}	-0.244***	(-4.44)	ALL_{t-1}	-8.239***	(-3.06)	1053.478***	(50.23)
$\Delta UNEMP_{t-1}$	0.001	(0.22)	NPL_{t-1}	5.050***	(6.16)	-74.855***	(-10.84)
			NCO_t	607.730***	(36.92)		
			ΔNPL_t	17.239***	(4.79)		
			$D\Delta NPL_t$	-0.056***	(-2.91)		
			$D\Delta NPL_t \times \Delta NPL_t$	-8.854**	(-2.11)		
			$LOANS_t$	0.772***	(8.51)	1.048	(1.59)
			$\Delta LOANS_t$	2.191***	(10.79)	3.886***	(3.45)
			$EBTLLP_t$	28.879***	(7.36)	45.096	(1.37)
			$AVENCO_t$			304.361**	(2.36)
			NPL_t			75.944***	(11.11)
			$TIER1_{t-1}$	0.397*	(1.75)	6.037**	(2.05)
			$CILNS_t$	0.493***	(3.24)	0.719	(0.47)
			$CSLNS_t$	2.013***	(7.57)	3.256**	(2.02)
			$RESRELNS_t$	-0.401***	(-5.54)	-0.640	(-1.09)
			$FMRELNS_t$	-0.301***	(-2.84)	0.802*	(1.73)
			$AGLNS_t$	-0.231**	(-2.17)	-1.043*	(-1.85)
			$\Delta GDPt$	0.123	(0.71)	-0.185	(-0.34)
			$\Delta UNEMP_t$	0.023**	(2.42)	0.180***	(5.18)
			GDP_{t-1}	0.075	(0.97)	0.420**	(2.09)
			EDU_{t-1}	-0.000***	(-2.85)	-0.000**	(-2.55)
			$MARITAL_{t-1}$	0.461	(1.25)	1.675	(1.33)
Constant	-4.913***	(-36.79)	*Constant*	-1.821	(-1.54)	-9.906***	(-2.75)
County-Quarter FE	Yes		County-Quarter FE	Yes		Yes	
R-squared	0.82		R-squared	0.49		0.85	
N	95,436		N	95,436		95,436	

This table reports the results from a reverse causality minimization analysis. Column 1 regresses the lagged CBA variable (CBA_t) on controls and lagged LLP (LLP_{t-1}), generating both fitted and residualized lagged CBA. Columns 2 and 3 use the fitted and residual components of lagged CBA to predict LLP and ALL, respectively. All models include county, and year-quarter fixed effects. Robust standard errors are clustered on banks. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively, based on a two-tailed test. T-statistics are reported in parentheses. Continuous variables are winsorized at the 1% level. LLP and ALL variables are scaled by 1,000 for display purposes. Subscript i is omitted to conserve space.

Table 8
Oster (2019) tests.

Panel A: Oster (2019) Tests for Main Regression Models

	(1) Oster Test with LLP (scaled by 1,000) as Dependent Var		(2)		(3) Oster Test with ALL (scaled by 1,000) as Dependent Var		(4)	
	Baseline Regression		Full Regression		Baseline Regression		Full Regression	
CBA_{t-1}	0.022**	(2.15)	0.037***	(3.14)	0.257***	(14.58)	0.107**	(2.33)
NPL_{t-1}	2.369***	(3.07)	4.381***	(5.55)	-46.675***	(-10.55)	-75.143***	(-10.67)
$LOANS_t$	0.341***	(4.80)	0.614***	(7.48)	-0.589**	(-2.55)	-0.661	(-0.97)
$\Delta LOANS_t$	2.965***	(13.95)	2.399***	(10.64)	5.540***	(11.90)	4.592***	(3.60)
NCO_t	624.606***	(36.99)	601.023***	(37.42)				
ΔNPL_t	16.997***	(5.40)	17.901***	(5.29)				
$D\Delta NPL_t$	-0.068***	(-3.78)	-0.058***	(-3.14)				
$D\Delta NPL_t \times \Delta NPL_t$	-10.303***	(-2.59)	-10.355***	(-2.59)				
ALL_{t-1}	-2.986	(-1.21)	-5.337**	(-2.04)			1055.7***	(45.55)
$CRISK_{t-1}$			-0.005	(-1.00)			-0.030*	(-1.93)
$AVENCO_t$					-42.066	(-0.88)	309.210**	(2.25)
NPL_t					66.684***	(12.78)	75.569***	(11.50)
$SIZE_{t-1}$			-0.027**	(-2.43)	-0.150***	(-5.54)	6.027**	(2.05)
$EBTLLP_t$			27.727***	(7.09)	66.109***	(6.42)	59.397*	(1.94)
$TIER1_{t-1}$			0.623***	(2.73)	0.000***	(4.56)	0.000***	(3.07)
$CILNS_t$			0.558***	(3.62)			0.538	(0.34)
$CSLNS_t$			1.987***	(7.71)			3.317*	(1.80)
$RESRELNS_t$			-0.340***	(-5.35)			-0.122	(-0.35)
$FMRELNS_t$			-0.278***	(-2.75)			0.474	(1.11)
$AGLNS_t$			-0.285***	(-2.77)			-1.042**	(-2.07)
$\Delta GDPt$			-0.030	(-0.20)			0.212	(0.43)
$\Delta UNEMP_t$			0.073***	(5.87)			0.103***	(2.77)
GDP_{t-1}			0.006	(0.08)			0.055	(0.20)
EDU_{t-1}			-0.000***	(-2.98)			-0.000***	(-2.89)
$MARITAL_{t-1}$			0.525*	(1.65)			1.276	(1.11)
Constant	0.077	(1.26)	-0.262	(-0.24)	2.699***	(7.91)	0.712	(0.17)
Delta (Oster, 2019)	**9.3016**	**5.8268**						
R-squared	0.46		0.48		0.83		0.84	
County-quarter FE	Yes		Yes		Yes		Yes	
N	95,436		95,436		95,436		95,436	

Panel B: Coefficient Estimates and Oster Test Results Across Key Models:

Table	Specification	Dependent Variable	Coefficient	Oster Delta
2	CBA and LLP	LLP	0.043***	9.3016
3	CBA and ALL	ALL	0.110**	5.8268
6	CBA and LLP - low climate risk subsample	LLP	0.038**	6.6807
6	CBA and ALL - low climate risk subsample	ALL	0.174**	2.6418
6	CBA and LLP - high climate risk subsample	LLP	0.031**	12.0315
6	CBA and ALL - high climate risk subsample	ALL	0.191**	5.4872
9A	Subsample tests (Deposit_Percent = 100%)	LLP	0.067***	1.4792
9A	Subsample tests (Deposit_Percent = 100%)	ALL	0.222***	1.8161
9A	Subsample tests (Deposit_Percent ≥ 90%)	LLP	0.044**	1.7131
9A	Subsample tests (Deposit_Percent ≥ 90%)	ALL	0.219***	1.7262
9B	Subsample tests (Post-COVID)	LLP	0.017*	7.9458
9B	Subsample tests (Post-COVID)	ALL	0.139***	4.2304
9B	Subsample tests (Pre-COVID)	LLP	0.009**	4.146
9B	Subsample tests (Pre-COVID)	ALL	0.107***	13.7467
10	CBA and Bank Risk-Taking	NELPR	-0.015***	0.5465
10	CBA and Bank Risk-Taking	ZSCORE	-0.034***	10.6456
10	CBA and Bank Risk-Taking	NIM	-0.003*	3.4215

This table reports the results from an Oster (2019) omitted variables bias test to assess the robustness of the relation between CBA and LLP/ALL. R-squared max (assumed) is 1 for both models. Columns 1 and 2 use LLP as the dependent variable, and columns 3 and 4 use ALL. For each outcome, the baseline regression includes a limited set of controls, while the full regression incorporates the complete set. The Delta is then computed as per Oster (2019). Robust standard errors are clustered at the bank level. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests. T-statistics are in parentheses. Subscript *i* is omitted to conserve space.

This table reports estimates for coefficient of CBA and the corresponding Oster (2019) Delta values for key regressions. Variables used for the base models (i.e., the restricted models) are consistent with Table 8 Panel A. The full regression models are consistent with the models used in the corresponding tables identified in the Table column. We compare the full models to the corresponding restricted models and use the change in the coefficient and R-squared to compute the Oster Delta. All robust standard errors are clustered at the bank level. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests. Subscript i is omitted to conserve space.

Table 9
Additional robustness tests.

Panel A: Subsample Tests Based on Banks' Branch Deposits' Percentage in the County

	(1)		(2)		(3)		(4)	
Dependent Variable	LLP_t		ALL_t		LLP_t		ALL_t	
Subsample	Deposit_Percent = 100%	Deposit_Percent = 100%	Deposit_Percent ≥ 90%	Deposit_Percent ≥ 90%				
CBA_{t-1}	**0.067*** **	**(2.89)**	**0.222*** **	**(2.69)**	**0.044** **	**(2.02)**	**0.219*** **	**(2.76)**
$CRISK_{t-1}$	-0.005	(-0.52)	-0.021	(-0.77)	-0.006	(-0.74)	-0.019	(-0.81)
$SIZE_{t-1}$	-0.010	(-0.34)	-0.298*	(-1.82)	-0.033	(-1.29)	-0.252*	(-1.90)
ALL_{t-1}	-1.968	(-0.45)	1097.251***	(32.14)	-1.953	(-0.48)	1083.675***	(35.49)
NPL_{t-1}	4.150***	(3.55)	-61.937***	(-6.46)	4.312***	(3.97)	-67.441***	(-7.12)
ΔNPL_t	15.074***	(3.28)			15.638***	(3.61)		
$D\Delta NPL_t$	-0.074**	(-2.30)			-0.075***	(-2.60)		
$D\Delta NPL_t \times \Delta NPL_t$	-15.089***	(-3.34)			-13.133***	(-2.76)		
$LOANS_t$	0.614***	(4.13)	-1.434	(-1.30)	0.632***	(4.71)	-1.408	(-1.46)
$\Delta LOANS_t$	2.916***	(7.89)	5.185***	(2.63)	2.939***	(8.45)	4.947***	(2.81)
$EBTLLP_t$	24.501***	(4.36)	56.125	(1.38)	25.811***	(4.99)	52.582	(1.43)
NCO_t	595.300***	(24.39)			592.099***	(26.02)		
$TIER1_{t-1}$	0.469	(1.52)	6.842**	(2.41)	0.533*	(1.83)	6.278**	(2.38)
$CILNS_t$	0.913***	(3.33)	1.122	(0.55)	0.858***	(3.42)	1.128	(0.61)
$CSLNS_t$	2.277***	(5.39)	5.705**	(1.99)	2.254***	(5.94)	5.297**	(2.09)
$RESRELNS_t$	-0.166	(-1.31)	0.203	(0.41)	-0.203*	(-1.83)	0.218	(0.53)
$FMRELNS_t$	-0.200	(-1.13)	0.521	(0.62)	-0.122	(-0.72)	0.726	(0.98)
$AGLNS_t$	-0.320*	(-1.70)	-1.360	(-1.42)	-0.367**	(-2.06)	-1.325	(-1.53)
$\Delta GDPt$	0.140	(0.50)	0.116	(0.13)	0.273	(0.97)	0.368	(0.40)
$\Delta UNEMP_t$	0.010	(0.52)	0.024	(0.41)	0.019	(1.01)	0.070	(1.23)
$AVENCO_t$			346.619*	(1.72)			313.491*	(1.73)
NPL_t			59.430***	(5.64)			66.531***	(6.43)
Constant	-0.297	(-0.70)	2.128	(0.97)	-0.026	(-0.07)	1.822	(0.99)
County-Quarter FE	Yes		Yes		Yes		Yes	
R-squared	0.51		0.84		0.50		0.85	
N	39,385		39,335		45,745		45,694	

Panel B: Subsample Tests in post-COVID vs. pre-COVID Years

	(1)		(2)		(3)		(4)	
	LLP_t		ALL_t		LLP_t		ALL_t	
Subsample	Year ≥ 2020		Year ≥ 2020		Year < 2020		Year < 2020	
CBA_{t-1}	**0.017* **	**(1.67)**	**0.139*** **	**(3.03)**	**0.009** **	**(2.13)**	**0.107*** **	**(2.83)**
$CRISK_{t-1}$	-0.006	(-1.13)	-0.049***	(-2.79)	0.004**	(2.03)	-0.003	(-0.28)
$SIZE_{t-1}$	0.087***	(4.13)	-0.128*	(-1.71)	-0.028***	(-3.08)	-0.144***	(-3.20)
ALL_{t-1}	7.005	(1.38)	1100.758***	(32.13)	-3.398	(-1.45)	1066.865***	(47.31)
NPL_{t-1}	2.526	(1.20)	-42.419***	(-3.86)	4.123***	(5.09)	-77.317***	(-10.31)
ΔNPL_t	16.148*	(1.68)			18.135***	(4.84)		
$D\Delta NPL_t$	-0.053	(-1.31)			-0.061***	(-2.87)		
$D\Delta NPL_t \times \Delta NPL_t$	-9.374	(-0.68)			-9.189**	(-1.98)		
$LOANS_t$	1.039***	(6.93)	0.953	(1.16)	0.624***	(8.16)	-0.171	(-0.32)
$\Delta LOANS_t$	1.925***	(4.32)	1.274	(0.60)	2.553***	(9.67)	4.163***	(3.09)
$EBTLLP_t$	39.808***	(4.97)	93.308**	(2.40)	28.404***	(6.55)	61.595*	(1.66)
NCO_t	653.793***	(15.72)			632.680***	(34.97)		
$TIER1_{t-1}$	0.650	(1.14)	7.369**	(2.35)	0.683***	(3.18)	5.051*	(1.94)
$CILNS_t$	1.062***	(3.31)	0.143	(0.07)	0.425***	(2.90)	1.534	(1.06)
$CSLNS_t$	1.534***	(3.86)	4.655**	(2.42)	1.845***	(8.38)	2.806*	(1.85)
$RESRELNS_t$	-0.295**	(-1.99)	0.371	(0.50)	-0.275***	(-5.64)	0.922*	(1.70)
$FMRELNS_t$	-0.576***	(-3.28)	0.400	(0.73)	-0.119	(-1.62)	0.791***	(2.66)

(*continued on next page*)

Table 9 (*continued*)

Panel A: Subsample Tests Based on Banks' Branch Deposits' Percentage in the County

	(1)		(2)		(3)		(4)	
$AGLNS_t$	-0.447***	(-2.68)	-1.863***	(-2.80)	0.021	(0.31)	-0.148	(-0.52)
$\Delta GDPt$	0.497	(1.09)	1.820	(1.56)	0.035	(0.20)	-0.012	(-0.02)
$\Delta UNEMP_t$	0.007	(0.52)	0.086**	(2.41)	0.031*	(1.95)	0.013	(0.24)
$AVENCO_t$			1044.704***	(3.51)			241.981*	(1.70)
NPL_t			29.195**	(2.41)			76.324***	(9.83)
Constant	-1.609***	(-5.16)	-0.978	(-0.91)	-0.059	(-0.47)	-0.260	(-0.44)
County FE	No		No		No		No	
Year-Quarter FE	Yes		Yes		Yes		Yes	
R-squared	0.45		0.79		0.47		0.82	
N	9,826		9,826		85,610		85,610	

Panel C: Alternative Measures of CBA

	(1)		(2)		(3)		(4)	
	LLP_t		ALL_t		LLP_t		ALL_t	
CBA_ALT_{t-1}	**0.050*** **	**(5.47)**	**0.080*** **	**(2.79)**				
CBA_WTD_{t-1}					**0.017*** **	**(2.69)**	**0.157*** **	**(4.73)**
$CRISK_{t-1}$	-0.017**	(-2.54)	-0.030**	(-2.09)	-0.001	(-0.18)	-0.044***	(-3.22)
$SIZE_{t-1}$	-0.007	(-0.58)	-0.251***	(-2.83)	-0.030***	(-2.60)	-0.220***	(-2.80)
ALL_{t-1}	-0.923	(-0.29)	1066.883***	(36.99)	-5.910**	(-2.19)	1054.406***	(49.24)
NPL_{t-1}	3.936***	(3.90)	-61.763***	(-9.48)	4.173***	(5.17)	-72.074***	(-10.75)
ΔNPL_t	16.188***	(3.65)			18.708***	(5.49)		
$D\Delta NPL_t$	-0.066***	(-2.69)			-0.057***	(-3.03)		
$D\Delta NPL_t \times \Delta NPL_t$	-12.556**	(-2.27)			-11.590***	(-2.72)		
$LOANS_t$	0.662***	(7.25)	-0.264	(-0.35)	0.615***	(7.31)	-0.534	(-0.81)
$\Delta LOANS_t$	2.796***	(11.37)	3.905**	(2.49)	2.377***	(10.48)	4.308***	(3.53)
$EBTLLP_t$	25.556***	(5.66)	75.661**	(2.32)	27.617***	(6.80)	59.658**	(1.97)
NCO_t	647.887***	(33.69)			602.430***	(36.88)		
$TIER1_{t-1}$	0.705***	(2.75)	6.436**	(2.27)	0.616**	(2.53)	5.966**	(2.21)
$CILNS_t$	0.874***	(4.98)	1.218	(0.67)	0.569***	(3.47)	1.250	(0.80)
$CSLNS_t$	1.973***	(7.49)	2.832	(1.49)	2.019***	(7.68)	3.102*	(1.80)
$RESRELNS_t$	-0.238***	(-3.15)	-0.267	(-0.79)	-0.322***	(-4.90)	0.011	(0.03)
$FMRELNS_t$	-0.346***	(-3.00)	0.085	(0.19)	-0.233**	(-2.21)	0.744*	(1.83)
$AGLNS_t$	-0.057	(-0.49)	-0.888*	(-1.70)	-0.254**	(-2.38)	-0.835*	(-1.73)
$\Delta GDPt$	-0.155	(-0.75)	-0.306	(-0.53)	-0.006	(-0.04)	0.467	(1.02)
$\Delta UNEMP_t$	0.086***	(12.59)	0.132***	(7.53)	0.073***	(5.84)	0.211***	(8.03)
$AVENCO_t$			420.384**	(2.37)			266.270**	(2.09)
NPL_t			59.585***	(8.81)			72.128***	(12.30)
Constant	-0.760***	(-3.78)	0.627	(0.59)	0.094	(0.55)	1.691*	(1.66)
County FE	Yes		Yes		Yes		Yes	
Year-Quarter FE	Yes		Yes		Yes		Yes	
R-squared	0.52		0.84		0.48		0.85	
N	95,436		95,436		95,436		95,436	

Panel D: Alternative Measures of Climate Risk.

	(1)		(2)		(3)		(4)		(5)		(6)	
Dependent Variable	LLP_t		ALL_t		LLP_t		ALL_t		LLP_t		ALL_t	
Measures of CRISK	*CDD*		*CDD*		*CRISK_5YRS*	*CRISK_5YRS*	*CRISK_RARE*	*CRISK_RARE*				
CBA_{t-1}	**0.048*** **	**(8.12)**	**0.090*** **	**(4.73)**	**0.039*** **	**(3.59)**	**0.095** **	**(2.20)**	**0.039*** **	**(3.54)**	**0.098** **	**(2.31)**
$CRISK\ MEASURES_{t-1}$	0.000	(0.85)	0.000	(1.03)	0.005	(1.05)	-0.038*	(-1.66)	-0.002	(-0.24)	-0.011	(-0.47)
$SIZE_{t-1}$	-0.013	(-1.22)	-0.130	(-1.50)	-0.027**	(-2.38)	-0.232***	(-2.89)	-0.027**	(-2.38)	-0.232***	(-2.89)
ALL_{t-1}	-7.530***	(-3.38)	1031.6***	(41.14)	-5.959**	(-2.24)	1056.6***	(45.67)	-5.970**	(-2.24)	1056.6***	(45.66)
NPL_{t-1}	3.014***	(3.23)	-72.27***	(-9.21)	4.593***	(5.61)	-71.571***	(-10.63)	4.597***	(5.61)	-71.584***	(-10.63)
ΔNPL_t	18.547***	(3.95)			16.976***	(4.94)			16.973***	(4.94)		

(*continued on next page*)

Table 9 (*continued*)

Panel A: Subsample Tests Based on Banks' Branch Deposits' Percentage in the County												
	(1)		(2)		(3)		(4)					
$D\Delta NPL_t$	-0.040**	(-2.45)			-0.059***	(-3.11)			-0.059***	(-3.11)		
$D\Delta NPL_t \times \Delta NPL_t$	-6.081	(-1.03)			-8.890**	(-2.13)			-8.880**	(-2.12)		
$LOANS_t$	0.399***	(4.98)	-0.631*	(-1.67)	0.634***	(7.63)	-0.651	(-0.97)	0.634***	(7.62)	-0.650	(-0.97)
$\Delta LOANS_t$	3.421***	(11.84)	2.736***	(4.03)	2.528***	(11.51)	4.399***	(3.52)	2.530***	(11.50)	4.389***	(3.50)
$EBTLLP_t$	15.200***	(3.74)	39.660	(1.54)	28.066***	(7.25)	57.727*	(1.88)	28.064***	(7.25)	57.719*	(1.88)
NCO_t	606.7***	(26.55)			603.9***	(36.98)			603.98***	(36.98)		
$TIER1_{t-1}$	0.693***	(3.00)	2.168	(1.29)	0.638***	(2.67)	6.072**	(2.10)	0.638***	(2.67)	6.074**	(2.10)
$CILNS_t$	0.925***	(6.27)	1.530	(1.12)	0.553***	(3.65)	1.375	(0.86)	0.553***	(3.65)	1.380	(0.86)
$CSLNS_t$	1.288***	(5.20)	1.049	(1.29)	1.965***	(7.60)	3.266*	(1.77)	1.963***	(7.60)	3.276*	(1.78)
$RESRELNS_t$	-0.216***	(-3.70)	0.187	(0.76)	-0.359***	(-5.57)	0.060	(0.17)	-0.359***	(-5.57)	0.058	(0.17)
$FMRELNS_t$	0.065	(0.55)	0.775*	(1.94)	-0.320***	(-3.11)	0.609	(1.41)	-0.321***	(-3.12)	0.616	(1.42)
$AGLNS_t$	-0.155	(-1.21)	-0.330	(-0.71)	-0.280***	(-2.73)	-0.858*	(-1.74)	-0.279***	(-2.72)	-0.866*	(-1.76)
$\Delta GDPt$	0.245	(1.24)	0.651	(0.90)	0.049	(0.28)	-0.334	(-0.61)	0.048	(0.27)	-0.323	(-0.59)
$\Delta UNEMP_t$	0.108***	(16.13)	0.112***	(4.28)	0.032***	(3.69)	0.125***	(4.07)	0.032***	(3.68)	0.125***	(4.07)
GDP_{t-1}	-0.022***	(-3.48)	-0.053**	(-2.36)	0.081	(1.11)	0.508**	(2.56)	0.084	(1.15)	0.486**	(2.47)
EDU_{t-1}	0.000	(1.08)	0.000	(0.99)	-0.000***	(-3.44)	-0.000***	(-2.73)	-0.000***	(-3.41)	-0.000***	(-2.82)
$MARITAL_{t-1}$	0.267*	(1.83)	-0.472	(-0.51)	0.173	(0.56)	1.152	(1.17)	0.161	(0.53)	1.228	(1.22)
$AVENCO_t$			41.311	(0.47)			271.801**	(2.04)			271.281**	(2.03)
NPL_t			72.957***	(9.18)			72.311***	(10.14)			72.299***	(10.14)
Constant	0.248	(1.31)	1.961*	(1.68)	-1.255	(-1.11)	-6.594*	(-1.91)	-1.284	(-1.14)	-6.346*	(-1.85)
State-Quarter FE	Yes		Yes		No		No		No		No	
County-Quarter FE	No		No		Yes		Yes		Yes		Yes	
Adj. R-squared	0.40		0.87		0.49		0.85		0.49		0.85	
N	95,436		95,436		95,436		95,436		95,436		95,436	

This table reports the relationship between LLP/ALL and CBA. Regressions are conducted on subsamples of banks based on the percentage of their branch deposits located within a single operating county. Columns 1 and 2 include only banks whose branch deposits are entirely (100%) concentrated in one county. Columns 3 and 4 include banks with over 90% of branch deposits in a single county. All models include county, year, and quarter fixed effects. Robust standard errors are clustered at the bank level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests. T-statistics are reported in parentheses. All continuous variables are winsorized at the 1% level. Dependent variables are scaled by a factor of 1,000 for display purposes. Subscript *i* is omitted to conserve space.

This table reports the relationship between LLP/ALL and CBA. Regressions are conducted on subsamples of banks based on before or after COVID years. Columns 1 and 2 include only observations after COVID (i.e., Year ≥ 2020). Columns 3 and 4 include observations before COVID (i.e., Year < 2020). All models include county, year, and quarter fixed effects. Robust standard errors are clustered at the bank level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests. T-statistics are reported in parentheses. All continuous variables are winsorized at the 1% level. Dependent variables are scaled by a factor of 1,000 for display purposes. Subscript *i* is omitted to conserve space.

This table reports the relationship between LLP/ALL and CBA with alternative measures of CBA. Columns 1 and 2 use CBA_ALT as the measure of CBA. Columns 3 and 4 use CBA_WTD as the measure of CBA. All models include county, year, and quarter fixed effects. Robust standard errors are clustered at the bank level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests. T-statistics are reported in parentheses. All continuous variables are winsorized at the 1% level. Dependent variables are scaled by a factor of 1,000 for display purposes. Subscript *i* is omitted to conserve space.

This table reports the relation between CBA and LLP/ALL, with alternative measures of climate risk in control variables. Columns 1 and 2 use CDD_{t-1} as the measure of climate risk. Columns 3 and 4 use $CRISK\_5YRS_{t-1}$ as the measure of climate risk. Columns 5 and 6 use $CRISK\_RARE_{t-1}$ as the measure of climate risk. Columns 1 and 2 include state, year, and quarter fixed effects (because of multicollinearity issues when county fixed effects are applied). Columns 3 to 6 include county, year, and quarter fixed effects. Robust standard errors are clustered on banks. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively, based on a two-tailed test. T-statistics are reported in parentheses. Continuous variables are winsorized at the 1% level. Dependent variables (in regression) are scaled by multiplying 1,000 for display purposes. Subscript *i* is omitted to conserve space.

Table 10
CBA and bank risk-taking.

	(1)			(2)		(3)	
	$NELPR_t$			***$ZSCORE_{t/t\text{-}3}$***		***$\sigma NIM_{t/t\text{-}3}$***	
$CBA_{t\text{-}1}$	**-0.015*****	**(-4.61)**	***$CBA_{t\text{-}1}$***	**-0.034*****	**(-6.00)**	**-0.003***	**(-1.82)**
$CRISK_{t\text{-}1}$	0.009***	(3.97)	$CRISK_{t\text{-}1}$	0.017***	(3.64)	0.002*	(1.70)
$SIZE_{t\text{-}1}$	0.018*	(1.69)	$SIZE_{t/t\text{-}3}$	-1.144***	(-141.3)	-0.073***	(-5.58)
$ALL_{t\text{-}1}$	-4.311**	(-2.37)	$ALL_{t/t\text{-}3}$	5.173***	(3.26)	1.906***	(2.75)
$NPL_{t\text{-}1}$	1.081***	(2.68)	$NPL_{t/t\text{-}3}$	9.842***	(16.47)	-0.669***	(-4.32)
ΔNPL_t	-0.024	(-0.09)	$LLP_{t/t\text{-}3}$	-0.688	(-0.08)	-3.023	(-0.63)
$\Delta NPL_{t\text{-}1}$	-0.175	(-0.69)	$\Delta LOAN\%_{t/t\text{-}4}$	3.657***	(16.18)	0.812***	(25.46)
$LOANS_t$	1.874***	(21.35)	$NCO_{t/t\text{-}3}$	39.604***	(4.32)	17.750***	(5.98)
$REVG_t$	0.000	(0.49)	$REVG_{t/t\text{-}4}$	-0.000	(-0.25)	0.000	(0.62)
$\Delta LOAN\%_t$	-0.213***	(-2.91)	$TIER1_{t/t\text{-}3}$	-0.659***	(-6.87)	0.120*	(1.65)
$EBTLLP_t$	-18.887***	(-6.49)	$CILNS_{t/t\text{-}3}$	0.349***	(3.12)	-0.063	(-0.72)
NCO_t	3.365	(1.58)	$CSLNS_{t/t\text{-}3}$	0.667***	(4.22)	0.163	(1.26)
$TIER1_{t\text{-}1}$	-0.783***	(-2.86)	$RESRELNS_{t/t\text{-}3}$	0.084	(1.18)	-0.140**	(-2.29)
$CILNS_t$	-0.575***	(-3.59)	$FMRELNS_{t/t\text{-}3}$	-0.418***	(-3.37)	0.070	(1.04)
$CSLNS_t$	-1.383***	(-12.59)	$AGLNS_{t/t\text{-}3}$	0.354***	(2.88)	-0.077	(-0.98)
$RESRELNS_t$	0.234***	(6.03)	$\Delta GDP_{t/t\text{-}3}$	0.032	(0.10)	0.154**	(2.42)
$FMRELNS_t$	-1.645***	(-22.18)	$\Delta UNEMP_{t/t\text{-}3}$	0.253***	(16.80)	0.024***	(5.68)
$AGLNS_t$	-0.343***	(-5.81)					
ΔGDP_t	0.082	(1.41)					
$\Delta UNEMP_t$	-0.006***	(-2.96)					
Constant	-3.349***	(-15.25)	Constant	-3.316***	(-26.68)	1.483***	(8.40)
Regression Coefficients and T-stats with Standardized Variables (Selected):							
$CBA_{t\text{-}1}$	**-0.044*****	**(-4.61)**	***$CBA_{t\text{-}1}$***	**-0.036*****	**(-6.00)**	**-0.016***	**(-1.82)**
$CRISK_{t\text{-}1}$	0.021***	(3.97)	$CRISK_{t\text{-}1}$	0.0013	(3.64)	0.007*	(1.70)
Adjusted R2	0.81		R-squared	0.80		0.84	
N	95,346		N	95,436		95,436	

This table reports the relationship between bank risk-taking and CBA. Bank risk-taking is proxied by three measures, namely, the negative of the equity-to-loan portfolio risk ratio (*NELPR*) following Lee et al. (2024) in Column 1, the negative logarithm of Z-Score (*ZSCORE*) in Column 2, and the standard deviation of net interest margin (*σNIM*) in Column 3. All columns are controlled for climate risk. All columns include county-year-quarter level fixed effects. Robust standard errors are clustered on banks. Detailed variable definitions are in Appendix A. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively, based on a two-tailed test. T-statistics are reported in parentheses. Continuous variables are winsorized at the 1% level. Subscript *i* is omitted to conserve space.

Table 11
The role of CBA on bank risk-taking and climate risk
(Note: The interaction term uses mean-centered CBA).

	(1)		(2)			(3)		(4)	
	$NELPR_t$		***$NELPR_t$***			***$ZSCORE_{t/t\text{-}3}$***		***$ZSCORE_{t/t\text{-}3}$***	
$CRISK_{t\text{-}1}$	0.013***	(5.12)	0.009***	(5.95)	***$CRISK_{t\text{-}1}$***	0.024***	(9.84)	0.016***	(3.53)
$CBA\_MC_{t\text{-}1}$			-0.013***	(-3.71)	***$CBA\_MC_{t\text{-}1}$***			-0.026***	(-3.77)
$CRISK_{t\text{-}1} \times CBA\_MC_{t\text{-}1}$			**-0.002*****	**(-3.59)**	***$CRISK_{t\text{-}1} \times CBA\_MC_{t\text{-}1}$***			-0.005**	(-2.43)
$SIZE_{t\text{-}1}$	0.020*	(1.84)	0.018**	(2.67)	$SIZE_{t/t\text{-}3}$	-1.120***	(-174.77)	-1.144***	(-111.2)
$ALL_{t\text{-}1}$	-3.896**	(-2.23)	-4.309***	(-6.99)	$NCO_{t/t\text{-}3}$	54.954***	(13.33)	39.794***	(3.84)
$NPL_{t\text{-}1}$	1.265***	(3.19)	1.091***	(5.65)	$LLP_{t/t\text{-}3}$	20.589***	(6.71)	-0.736	(-0.08)
ΔNPL_t	0.047	(0.17)	-0.022	(-0.05)	$NPL_{t/t\text{-}3}$	9.691***	(31.07)	9.869***	(16.03)
$\Delta NPL_{t\text{-}1}$	-0.165	(-0.68)	-0.179	(-0.40)	$ALL_{t/t\text{-}3}$	0.301	(1.25)	5.172***	(2.99)
$LOANS_t$	1.843***	(22.92)	1.874***	(23.77)	$RESRELNS_{t/t\text{-}3}$	-0.009	(-0.18)	0.084	(1.04)
$\Delta LOAN\%_t$	-0.221***	(-3.05)	-0.213***	(-4.52)	$TIER1_{t/t\text{-}3}$	-0.167	(-1.62)	-0.659***	(-7.73)
$EBTLLP_t$	-19.498***	(-6.73)	-18.893***	(-14.72)	$\Delta LOAN\%_{t/t\text{-}4}$	2.277***	(21.86)	3.657***	(15.81)
NCO_t	3.192	(1.54)	3.378***	(2.93)	$REVG_{t/t\text{-}4}$	-0.000	(-0.39)	-0.000	(-0.22)
$TIER1_{t\text{-}1}$	-0.787***	(-3.01)	-0.783***	(-2.97)	$FMRELNS_{t/t\text{-}3}$	-0.402***	(-4.56)	-0.415***	(-2.93)
$CILNS_t$	-0.585***	(-3.66)	-0.575***	(-15.57)	$AGLNS_{t/t\text{-}3}$	0.344***	(3.90)	0.351***	(2.69)
$CSLNS_t$	-1.401***	(-12.86)	-1.384***	(-46.26)	$CILNS_{t/t\text{-}3}$	0.225***	(3.21)	0.348***	(3.06)
$RESRELNS_t$	0.231***	(5.68)	0.234***	(11.90)	$CSLNS_{t/t\text{-}3}$	0.546***	(5.14)	0.664***	(3.55)
$FMRELNS_t$	-1.657***	(-22.85)	-1.644***	(-55.85)	$\Delta GDP_{t/t\text{-}3}$	0.953***	(5.68)	0.045	(0.14)
$AGLNS_t$	-0.339***	(-5.71)	-0.344***	(-21.92)	$\Delta UNEMP_{t/t\text{-}3}$	0.164***	(19.07)	0.252***	(16.24)
ΔGDP_t	0.020	(0.70)	0.081	(1.64)					
$\Delta UNEMP_t$	-0.017***	(-6.30)	-0.007	(-1.39)					
Constant	-3.345***	(-16.06)	-3.354***	(-18.65)	*Constant*	-3.496***	(-36.79)	-3.330***	(-20.03)
Adjusted R2	0.81		0.81		R-squared	0.78		0.80	
N	95,436		65,514		N	93,436		65,514	

This table reports the moderating role of CBA on bank risk-taking and climate risk. Bank risk-taking is proxied by *NELPR*. *CBA_MC* is the mean-centered version of *CBA*. All columns include county-year-quarter level fixed effects. Robust standard errors are clustered on banks. Detailed variable definitions are in Appendix A. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively, based on a two-tailed test. T-statistics are reported in parentheses. Continuous variables are winsorized at the 1% level. Subscript *i* is omitted to conserve space.

Table 12
CBA and bank risk-taking – alternative measures of CBA.

	(1)		(2)			(3)		(4)	
	$NELPR_t$		***$NELPR_t$***			***$ZSCORE_{t/t-3}$***		***$ZSCORE_{t/t-3}$***	
CBA_WTD_{t-1}	**-0.010*****	**(-3.69)**			***CBA_WTD_{t-1}***	**-0.009****	**(-2.28)**		
CBA_ALT_{t-1}			**-0.025*****	**(-4.85)**	***CBA_ALT_{t-1}***			**-0.030*****	**(-3.48)**
$CRISK_{t-1}$	0.011***	(4.78)	0.001	(0.29)	$CRISK_{t-1}$	0.023***	(4.89)	0.001	(0.09)
$SIZE_{t-1}$	0.020*	(1.87)	0.025	(1.39)	$SIZE_{t/t-3}$	-1.145***	(-141.07)	-1.133***	(-109.70)
ALL_{t-1}	-4.004**	(-2.27)	-9.669**	(-1.99)	$NCO_{t/t-3}$	37.966***	(4.39)	2.880	(0.22)
NPL_{t-1}	1.222***	(3.14)	1.864*	(1.87)	$LLP_{t/t-3}$	1.864	(0.22)	30.871***	(2.61)
ΔNPL_t	0.059	(0.22)	-0.052	(-0.12)	$NPL_{t/t-3}$	10.077***	(17.29)	10.071***	(11.58)
ΔNPL_{t-1}	-0.128	(-0.54)	-0.146	(-0.31)	$ALL_{t/t-3}$	5.672***	(3.39)	-1.568	(-0.79)
$LOANS_t$	1.848***	(22.79)	2.011***	(15.93)	$RESRELNS_{t/t-3}$	0.092	(1.30)	0.101	(1.11)
$\Delta LOAN\%_t$	-0.228***	(-3.17)	-0.433***	(-3.31)	$TIER1_{t/t-3}$	-0.644***	(-6.12)	-0.583***	(-5.88)
$EBTLLP_t$	-19.412***	(-6.74)	-14.189***	(-2.80)	$\Delta LOAN\%_{t/t-4}$	3.539***	(16.15)	3.529***	(11.91)
NCO_t	3.214	(1.55)	7.151	(1.11)	$REVG_{t/t-4}$	-0.001	(-1.22)	-0.001	(-0.76)
$TIER1_{t-1}$	-0.785***	(-3.02)	-0.584**	(-2.04)	$FMRELNS_{t/t-3}$	-0.427***	(-3.46)	-0.357**	(-2.30)
$CILNS_t$	-0.584***	(-3.67)	-0.523**	(-2.08)	$AGLNS_{t/t-3}$	0.335***	(2.74)	0.449***	(2.95)
$CSLNS_t$	-1.403***	(-12.90)	-1.334***	(-6.51)	$CILNS_{t/t-3}$	0.367***	(3.29)	0.468***	(3.35)
$RESRELNS_t$	0.229***	(5.63)	0.328***	(3.54)	$CSLNS_{t/t-3}$	0.674***	(4.28)	0.805***	(4.34)
$FMRELNS_t$	-1.660***	(-22.84)	-1.428***	(-10.21)	$\Delta GDP_{t/t-3}$	-0.478	(-1.38)	0.659	(1.25)
$AGLNS_t$	-0.344***	(-5.82)	-0.257*	(-1.83)	$\Delta UNEMP_{t/t-3}$	0.191***	(12.74)	0.309***	(15.90)
ΔGDP_t	-0.009	(-0.30)	0.024	(0.57)					
$\Delta UNEMP_t$	-0.017***	(-6.41)	-0.014***	(-4.87)					
Constant	-3.348***	(-16.08)	-3.571***	(-10.92)	*Constant*	-3.331***	(-26.53)	-3.416***	(-21.10)
Adjusted R2	0.75		0.85		R-squared	0.80		0.82	
N	95,436		95,436		N	93,436		95,436	

This table reports the relationship between bank risk-taking and CBA. Bank risk-taking is proxied by the negative of the equity-to-loan portfolio risk ratio (*NELPR*) in Columns 1 and 2, and by the negative of Z-score ($ZSCORE_t$) in Columns 3 and 4. CBA is proxied by CBA_WTD_{t-1} (Columns 1 and 3) and CBA_ALT_{t-1} (Columns 2 and 4). All columns include county-year-quarter level fixed effects. Robust standard errors are clustered on banks. Detailed variable definitions are in Appendix A. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively, based on a two-tailed test. T-statistics are reported in parentheses. Continuous variables are winsorized at the 1% level. Subscript *i* is omitted to conserve space.

credit risk management literature, demonstrating the importance CBA in conjunction with prudential loan loss provisioning in managing climate risk.

CRediT authorship contribution statement

Lorenzo Dal Maso: Writing – review & editing, Validation, Supervision, Resources, Methodology, Data curation, Conceptualization. **Xiaoran Jia:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Kiridaran Kanagaretnam:** Writing – review & editing, Writing – original draft, Supervision, Resources, Formal analysis, Conceptualization.

Declaration of competing interest

None.

Appendix A: Variables

$CBA_{i,t-1}$	=	Our main measure of climate change beliefs and attitudes. It is calculated as the first principal component extracted from a factor analysis of three variables from the county-level YCOM survey conducted by the Yale Program on Climate Change Communication (YPCCC). This measure follows Zhang et al. (2024), who use these three variables related to climate change beliefs and attitudes. The first factor has an eigenvalue of 2.83 (normalized eigenvalue = 0.9417) We select these variables because they are the survey questions available at the county level for years 2014, 2016, 2018, 2019, 2020, and 2021. The details of the variables are explained in Appendix B.
$CBA\_WTD_{i,t-1}$	=	Bank branch exposure (across counties, by deposits) weighted *CBA*.
$CBA\_HIGH_{i,t-1}$	=	A dummy variable equal to 1 if the $CBA_{i,t-1}$ is in the highest quartile across all county-years, and 0 if it is in the lowest quartile.
$CBA\_ALT_{i,t-1}$	=	Our alternative measure of climate change beliefs and attitudes. It is calculated as the first principal component extracted from a factor analysis of 12 variables (that contain data in the corresponding years as described in the variable description for $CBA_{i,t-1}$) from the county-level YCOM survey conducted by YPCCC. The first factor has an eigenvalue of 9.94 (normalized eigenvalue = 0.7508). The details of the variables are explained in Appendix B.
$\Delta CBA_{i,s/s-1}$	=	Changes in CBA derived from the previous survey results (CBA_{s-1}) to the CBA derived from the current survey (CBA_s) results.
$CRISK_{i,t-1}$	=	Proxy for climate risk following Dal Maso et al. (2024), measured as the number of natural disasters declared as major disasters over a 15-year span by the Federal Emergency Management Agency in each county-quarter.
$CDD_{i,t-1}$	=	Total county-wide property damages from all hazard types of climate disasters from 2010 to 2017 in millions of US dollars. Source: SHELDUS.
$CRISK\_5YRS_{i,t-1}$	=	Proxy for climate risk following Dal Maso et al. (2024), measured as the number of natural disasters declared as major disasters over a 5-year span by the Federal Emergency Management Agency in each county-quarter.
$CRISK\_RARE_{i,t-1}$	=	The number of natural disasters related to rare events declared as major disasters over a 15-year span by the Federal Emergency Management Agency in each county-quarter.
$CRISK\_HIGH_{i,t-1}$	=	A dummy equal to 1 if *CRISK* is in the highest quartile, and 0 if it is in the lowest quartile.
$NELPR_{i,t}$	=	The negative of the Equity-to-loan Portfolio Risk (ELPR) following Lee et al. (2024). NELPR measures the value at risk for a one-standard-deviation move in dollar-denominated default losses for the portfolio as a whole. The details of this measure is described in Section 3.4.
$ZSCORE_{i,t/t-3}$	=	Negative of log of (ROA + CAR) / σ(ROA) where ROA is earnings before taxes and provisions divided by lagged total assets, CAR is capital-asset ratio, and σ(ROA) is the standard deviation of ROA. ROA and CAR are calculated as the mean over the trailing four quarters. A higher Z-score implies higher risk-taking.
$\sigma NIM_{i,t/t-3}$	=	The standard deviation of net interest margin (NIM) over the trailing four quarters.
$ABALL_{i,t}$	=	The residual obtained from the following regression model following Beck and Narayanamoorthy (2013) and Jin et al. (2018): $ALL_{it} = \beta_0 + \beta_1 AVENCO_t + \beta_2 NPA_t + \beta_3 NPA_{t-1} + \beta_4 RESRELNS_t$

(*continued on next page*)

(*continued*)

		$+\beta_5 FMRELNS_t + \beta_6 AGLNS_t + \beta_7 CILNS_t + \beta_8 CSLNS_t + \beta_9 SIZE_{t-1}$ $+\beta_{10} TIER1_{t-1} + \beta_{11}\Delta LOANS_t + \beta_{12} EBTLLP_t + \beta_{13}\Delta UNEMP_t + Bank\ FE + Quarter\ FE + \varepsilon$ The residual is multiplied by 100 for display purposes.
$ABLLP_{i,t}$	=	*ABLLP* is discretionary, or abnormal, loan loss provisions, calculated as the residual from the models following Kanagaretnam et al. (2010) and Basu et al. (2020): $LLP_t = \alpha_0 + \alpha_1 ALL_{t-1} + \alpha_2 NPL_{t-1} + \alpha_3 LOAN_t + \alpha_4 \Delta LOAN\%_t + \alpha_5 NCO_t + \alpha_6 \Delta NPL_t \times D\Delta NPL_t + \alpha_6 \Delta NPL_t + \alpha_6 D\Delta NPL_t + \alpha_7 \Delta lnGDP_t + \alpha_8 \Delta UNEMP_t + Bank\ FE + Year\ FE + \varepsilon_{it}$. where *DΔNPL* is a dummy variable equal to 1 if the sign of *ΔNPL* is negative, and 0 otherwise; other variables are defined in Appendix A. The residual is multiplied by 100 for display purposes.
$LLP_{i,t}$	=	Provisions for credit losses divided by lagged (beginning) total loans.
$ALL_{i,t}$	=	Allowance for loan and lease losses divided by lagged total loans.
$AVECO_{i,t/t\text{-}3}$	=	The past four quarters' average net charge-offs (NCO) scaled by lagged total loans.
$NCO_{i,t}$	=	Net charge-offs (charge-offs less recoveries) divided by lagged total loans.
$NPL_{i,t}$	=	Nonperforming and non-accrual loans divided by lagged total loans.
$\Delta NPL_{i,t}$	=	Quarterly change in NPL.
$D\Delta NPL_{i,t}$	=	A dummy variable equal to 1 if *ΔNPL* is negative, and 0 otherwise.
$RESRELNS_{i,t}$	=	Residential real estate loans divided by total loans.
$FMRELNS_{i,t}$	=	Farmland real estate loans divided by total loans.
$AGLNS_{i,t}$	=	Agricultural loans divided by total loans.
$CILNS_{i,t}$	=	Commercial and industrial loans divided by total loans.
$CSLNS_{i,t}$	=	Consumer loans divided by total loans.
$SIZE_{i,t\text{-}1}$	=	Natural logarithm of lagged total assets.
$TIER_{i,t\text{-}1}$	=	Tier 1 capital ratio.
$LOANS_{i,t}$	=	Total loans scaled by lagged total assets.
$\Delta LOAN\%_{i,t}$	=	Quarterly percentage change in total loans.
$EBTLLP_{i,t}$	=	Earnings before tax and provisions divided by lagged total loans.
$REVG_{i,t}$	=	Quarterly revenue growth rate.
POP18	=	Natural logarithm of population of the over-18-year-old.
$GDP_{i,t}$	=	Annual gross domestic product in thousands at the county level.
$\Delta GDP_{i,t}$	=	Annual change in GDP.
$UNEMP_{i,t}$	=	Annual unemployment rate at the county level.
$\Delta UNEMP_{i,t}$	=	Annual change in UNEMP.
$EDU_{i,t}$	=	County-year level percentage of 18+ individuals with a bachelor's degree or above.
$MARITAL_{i,t}$	=	County-year level percentage of 15+ individuals who are currently married.

Appendix B: YCOM Survey Variables

Below is the list of the 12 county-year variables from YCOM data that we utilize to construct our measures of climate change beliefs and attitudes.

- To measure *CBA*, we use **"worried," "happening,"** and **"harmUS,"** which follows the Zhang et al. (2024) measure of "climate change social norms."
- To measure *CBA_ALT*, we use 12 variables with available data that cover the four dimensions of the YCOM survey.

1. Beliefs:
happening: Estimated percentage who think that global warming is happening.
human: Estimated percentage who think that global warming is caused mostly by human activities.
consensus: Estimated percentage who believe that most scientists think global warming is happening.
2. Risk Perceptions:
worried: Estimated percentage who are somewhat/very worried about global warming.
harmUS: Estimated percentage who think global warming will harm people in the U.S. a moderate amount/a great deal.
devharm: Estimated percentage who think global warming will harm people in developing countries a moderate amount/a great deal.
personal: Estimated percentage who think global warming will harm them personally a moderate amount/a great deal.
futuregen: Estimated percentage who think global warming will harm future generations a moderate amount/a great deal.
3. Policy Support
fundrenewables: Estimated percentage who somewhat/strongly support funding research into renewable energy sources.
CO2limits: Estimated percentage who somewhat/strongly support setting strict limits on existing coal-fired power plants.
regulate: Estimated percentage who somewhat/strongly support regulating CO2 as a pollutant.
4. Behaviors
discuss: Estimated percentage who discuss global warming occasionally/often with friends and family.

Data availability

Data will be made available on request.

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