Bank Reporting Decisions on Problem Loans: Evidence from Natural Disaster Responses[*]

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Abstract

Using natural disasters as shocks on local borrowers' solvency, we investigate how banks' post-shock reporting patterns of problem loans are affected by their existing asset quality. We find that local banks with high nonperforming loan ratios tend to report fewer problem loans in their financial statements upon facing natural disasters in the regions. These results are not driven by banks' real management to downsize their problem loans, such as expanding origination of safer loans and increasing loan charge-off. We conclude that banks' existing loan quality is an important driver underlying their use of accounting discretion to under-report problem loans.

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Introduction

As concerns for banks' asset quality increases after the Global Financial Crisis and recent Covid-19 pandemic, the growth and resolution of banks' troubled assets become one of key subjects attracting attentions from bank stakeholders and regulators.[1] This increased attention on distressed assets, particularly on nonperforming loans (NPLs)[2], is crucial since large and persistent NPL ratios[3] impede economic recovery as they adversely affect the soundness of the banking system and its ability to supply credits to the real economy (OECD [2021]; De Haan [2022]). To alleviate the heightened concerns and monitoring by stakeholders and regulators, bank managers may have an ex-ante incentive to use their accounting or real operational discretion to manage public reporting on bad loans at the cost of deviating from the normal course of decisions (Dechow, Ge and Schrand [2010]). Despite growing concerns for banks' asset quality, little attention has been paid to banks' reporting decisions on problem loans in their financial statements. In this study, we fill the gap by investigating whether banks with worse loan quality tend to use their accounting discretion to control expansion of their reported problem loans (i.e., nonperforming or non-accrual loans) following local natural disasters, which are employed as negative shocks on borrowers' overall solvency status.

If banks experience a decline in the overall quality of their loans as a result of adverse shocks to the solvency status of their borrowers, it is natural for the banks to recognize and report more problem loans. Greater problem loans reported in banks' financial statements will lead to a

[1] Centre for Economic Policy Research (2021) warns that European banks will face a wave of troubled loans after Covid-19 supports are ended. See details from here: https://cepr.org/voxeu/columns/preparing-wave-non-performing-loans-empirical-insights-and-important-lessons. Economic Governance Support Unit (2021) also discusses policy implications of a potential surge in nonperforming loans due to Covid-19. See details from here: https://www.europarl.europa.eu/RegData/etudes/STUD/2021/651387/IPOL_STU(2021)651387_EN.pdf
[2] Nonperforming loans are the sum of the loans more than 90 days past due (still accruing) and non-accrual loans. Non-accrual loans are the loans that are not accruing interest.
[3] NPL ratio is the ratio of a bank's nonperforming loans over its total loans.

larger cleaning up of their toxic assets, ultimately enabling the banks to absorb further adverse shocks in the future. An increase in troubled loans reported in the banks' financial statements, however, will be disclosed to the public and may be regarded as bad signals for the banks' overall asset quality. If the banks' existing asset quality prior to the negative shocks was poor, i.e., their NPL ratios are high, further growth of their problem loans following negative shocks can be taken as more serious adverse signals by the market participants and bank regulators. If the banks' managers have a concern for the market's or regulators' adverse responses to the rapid growth of problem loans, the managers may be reluctant to report emerging problem loans in financial statements and thus be incentivized to exploit their accounting discretion to control expansion of reported problem loans.

Although reporting a bank's problem loans in its financial statements is specified by regulatory guidance, managers' discretion is still available in classifying a loan as either performing or nonperforming (Liu and Ryan [1995]; Liu and Ryan [2006]). For example, an asset valuation or a business assessment is involved in identifying troubled or non-troubled assets. Banks may adjust the reporting timing of their problem loans either by finalizing their assessment quickly or by postponing it. As documented in Blattner, Farinha, and Rebelo (2020) and Chopra, Subramanian, and Tantri (2021), troubled loans can be rolled over or swapped with new loans to the same insolvent borrowers before the loans are further deteriorated or additional loan losses are recorded. Such a loan evergreening is another example of an accounting discretion used by the banks because this strategy is implemented to deliberately under-report the size of their current problem loans in their financial statements.

To test our prediction above, we employ a bank's NPL ratio as a variable that measures the bank's overall loan quality prior to the negative shocks. NPL ratios are considered an important summary measure indicating the banks' overall loan quality and riskiness and are widely used by bank regulators (e.g., Meeker and Gray [1987]).[4] Our study highlight the effects of a bank's existing NPL ratio on its financial reporting decision of problem loans in response to a negative shock on its asset quality, after controlling for the effects of the bank's capital adequacy and profitability, which prior studies largely focus on as main summary measure in banks (Beatty and Liao [2014]). In this study, we limit samples to local banks and use natural disasters as negative shocks on the solvency status of the banks' local borrowers. Each local bank is assigned to one county where at least 65 percent of its total deposits are collected, following the method used in Cortés (2014). We first confirm that if a natural disaster hits a county, the delinquency rate of the local bank in the affected area is more likely to rise in the current or following quarters.[5] This means that natural disasters are indeed negative shocks on borrowers' solvency status and banks' loan quality. In our regressions, we construct two-year event windows for each local bank, i.e., pre-period prior to the shock and post-period in the year of the natural disaster shock in the county. Our sample is further limited to the local banks located either in treated counties, which are affected by natural disasters, or in control counties, which are adjacent to the treated counties and do not face any natural disaster in the two-year window. We match local banks with high NPL ratios with those with low NPL ratios in nearby areas in their total asset sizes using nearest neighbor matching.

With this set-up, we first examine whether local banks with high NPL ratios (high NPL banks) tend to report fewer problem loans (nonperforming or non-accrual loans) than those with

[4] International regulatory bodies, such as the World Bank Group and the Basel Committee on Banking Supervision (hereafter BCBS), were in the process of developing internationally consistent and harmonized standards, such as the NPL ratio, for defining and supervising banks' overall loan quality (e.g., BCBS [2016]). According to "ECB Banking Supervision: Risk assessment for 2020", a high level of NPLs is one of major concerns for euro area banks by the European Central Bank (ECB). See details from here: https://www.bankingsupervision.europa.eu/ecb/pub/ra/html/ssm.ra2020~a9164196cc.en.html

[5] A loan is classified as a delinquent loan if payments of interest and/or the principal of the loan are past due for 30-90 days (but still accruing). High loan delinquency rate (total delinquent loans over total loans) can be regarded as an early warning for the bank's loan quality because a sizable number of delinquent loans are likely to become nonperforming loans in the near future. In untabulated results, we find a positive correlation between a bank's loan delinquency rate and its subsequent quarter's NPL ratio.

low NPL ratios (low NPL banks) upon facing natural disasters in the regions. Our regression results show that banks with high NPL ratios as of the pre-period are less likely to expand the amount of their reported nonperforming or non-accrual loans relative to those with low NPL ratios following local natural disasters. These results indicate that banks with high NPL ratios are more likely to prioritize curbing the amount of problem loans reported in their financial statements following the shocks. By contrast, the local banks with low NPL ratios tend to undergo significant expansion of their nonperforming/non-accrual loans on balance sheets following natural disasters in the regions. Our results remain robust to absorbing observable or unobservable time-varying bank-specific characteristics and year-specific factors by employing bank-level control variables, *Bank-Cohort* and *Year-Cohort* fixed effects.[6] As a further robustness test, we replace *Year-Cohort* fixed effect with *Year-Cohort-HighNPL* fixed effect to absorb any unobservable time-varying heterogeneity between the banks with high NPL ratios and those with low NPL ratios within the two-year window such as the differences in their inherent risk appetites, risk management systems, and regulatory scrutiny and find consistent results.[7] We further include *Year-County* fixed effect to absorb any county-level unobservable factors including local credit demands and economic conditions and find consistent results. By dynamic regressions with extended event windows, we confirm parallel pre-trends of banks' problem loan reporting patterns between high and low NPL banks prior to the shocks. We further find that high NPL banks' under-reporting of their problem loans is significant only in the year with the shocks and become insignificant in the following years.

Our results also remain robust to employing a set of different regression specifications. First, the results are robust to controlling for the effects of banks' existing capital adequacy and

[6] In the regression, we construct a cohort that includes observations in one treated county and those in its adjacent control counties. Local banks in a treated county and those in its adjacent control counties have the same cohort identifier in a two-year window.
[7] *HighNPL* is a dummy variable that takes a value of one for the bank with the high NPL ratio (above the median) as of the pre-period, zero otherwise.

profitability on their problem loan reporting. This implies that our results are indeed driven by the banks' existing asset quality measured by NPL ratios rather than their capital ratios or profitability documented in prior studies. Second, our results remain consistent when dummies for the banks' high/low NPL ratios are replaced with their quartile values. Third, we find that our results are more significant in the counties where monetary damages from natural disasters are greater. Fourth, our results remain consistent when we control for the effects of any unobservable characteristics shared by local banks affiliated in the same bank holding company (BHC) such as BHC-level ownership and governance structures by adding *Year-BHC* fixed effect. Fifth, the results are robust to using banks' NPL ratios instead of the size of their problem loans as the outcome variable. Finally, we find consistent results regardless of whether the banks are federally or state chartered.

Next, we examine potential alternative methods (i.e., real management) used to control the size of problem loans in banks' financial statements other than the use of accounting discretion. First, we examine whether banks with high NPL ratios deter the expansion of problem loans through changes in their credit portfolios in response to natural disasters. Following the shocks, the banks with high NPL ratios may aggressively reduce lending to borrowers with higher uncertainty or with higher default risks and focus on more creditworthy customers to control the expansion of troubled loans. To test this channel, we first investigate any differences between the banks with high and low NPL ratios in their subsequent lending activities (mortgages and small business loans) across diverse types of borrowers in response to local natural disasters. In our test results, however, we do not find any significant differences between banks with high and low NPL ratios in their loan origination across types (for example, loans to high or low income or loans with different purposes) following the shocks. We further examine whether changes in banks' lending-related asset structures after the shocks differ between the banks with high NPL ratios and those with low NPL ratios. Again, we do not find any empirical evidence for the differences between these two groups. We further confirm that no significant changes are made to high NPL local banks' liquidity creation (Berger and Bouwman, 2009) relative to those of low NPL local banks following natural disasters in the regions. Second, we examine whether banks' loan charge-off is the main driver used by the banks with high NPL ratios to deter the expansion of their reported problem loans following negative shocks. If a bank manager needs to reduce the reported problem loans due to concerns about its existing high NPL ratio, the bank may write off large fractions of its problem loans aggressively after the shocks. In contrast to this prediction, we cannot find any evidence that the banks with high NPL ratios tend to increase charge-offs for their existing loans than the banks with low NPL ratios do following the disasters. This implies that the banks with high NPL ratios do not use charge-off as a tool to control the size of their reported problem loans. Collectively, our empirical results do not support the prediction that banks with high NPL ratios curb the expansion of nonperforming or non-accrual loans in response to natural disasters through real management, such as issuing safer loans and promoting charge-off for existing toxic assets. The results indirectly indicate that the use of accounting discretion by bank managers can be the main driver underlying the reduction of the reported problem loans in their financial statements.

As the next step, we examine longer term consequences for the high NPL banks' reporting patterns of their problem loans and their balance sheet structure following natural disasters by extending the existing two-year event window to a four-year window (one for the pre-period and three years for the post-period). With this extended window, we no longer find the high NPL banks' under-reporting patterns of their problem loans in the long run. In contrast, interestingly, the high NPL banks are more likely to expand liquid assets and reduce loans in their total asset portfolios following natural disasters over the extended event window. Further, the high NPL banks reduce their liquidity creation from off-balance sheet items in the long run. The set of regression results show that high NPL banks tend to under-report their problem loans only in the short run following negative shocks but in the long run, they tend to downsize their credit and liquidity supply.

Lastly, we examine what motivates the banks with bad loan quality to under-report their problem loans following the shocks. We hypothesize that the possibility that such worse asset quality attracts attention from market participants or regulators could lead to the bank managers' decisions on accounting management to under-report their troubled loans. In other words, a bank's poor asset quality might trigger market discipline and supervisory engagement.[8] To empirically test this prediction, we focus on bank depositors as a bank's key stakeholder group and examine how they respond to banks' worsened loan quality. Our test results show that the local banks with high NPL ratios as of the pre-period are more likely to face reduction of their local deposits in the post-period. This effect is stronger during market stress periods, in competitive markets, and in regions with fewer banks. These results suggest that bank depositors indeed adversely respond to the bank's high NPL ratio. Correspondingly, we find that under-reporting of problem loans by the banks with high NPL ratios following negative shocks are also more pronounced in markets with financial distress, more competition, and fewer banks. From the sets of the regression results above, we conclude that stakeholders' adverse responses to the bank's poor asset quality may be one of the main reasons underlying the bank manager's strong incentive to under-report its problem loans in its financial statement following negative shocks on its local borrowers' overall credit quality.

The remainder of the paper is organized as follows. Section 1 reviews related literature. Section 2 provides the testable hypotheses of our study. Section 3 describes the empirical

[8] Banks' growing troubled assets may trigger the bank regulators' intervention. For example, ECB highlighted the rising NPLs as key risks facing euro area banks in "Guidance to banks on non-performing loans" (2017). In the guideline, the ECB requires high NPL banks to report their NPL strategy, which encompasses quantitative NPL targets and their corresponding operational plans, to national bank supervisors as well as the ECB. See details from here: https://www.bankingsupervision.europa.eu/ecb/pub/pdf/guidance_on_npl.en.pdf

methodology. Section 4 provides data sources and summary statistics. Section 5 presents the results. Section 6 concludes.

1. Literature Review

This paper is part of the literature that discusses why and how banks manage their accounting numbers. Prior studies focus on two specific accounting measures in banks' financial statements: capital ratios and earnings (Beatty and Liao [2014]). Banks' accounting management is particularly related to the banks' own goals to meet their required capital ratios or desired profitability indicators (Moyer [1990]; Beatty, Chamberlain and Magliolo [1995]; Ahmed, Takeda and Thomas [1999]; Laeven and Majnoni [2003]; Shrieves and Dahl [2003]; Huizinga and Laeven [2012]; Mariathasan and Merrouche [2014]; Begley, Purnanandam and Zheng [2017]; Ertan [2022]). Our paper contributes to this literature by highlighting that a bank's existing NPL ratio is another crucial indicator that the bank tries to maintain within a specific range, in addition to capital ratios and profitability. We document that a bank is incentivized to use its discretion to under-report its problem loans in its financial statement following negative shocks on local borrowers' overall solvency status if the bank's existing asset quality measured by its NPL ratio was bad prior to the shock.[9]

Our study is also closely related to prior studies that address the topic of banks' *zombie lending* phenomenon (lending to insolvent borrowers). Blattner, Farinha, and Rebelo (2020) document that Portuguese banks with capital ratios below the minimum requirement reallocate credit to distressed borrowers with under-reported loan losses during an economic downturn.

[9] More broadly, our paper is related to the literature that documents whether and how firm managers utilize their accounting or operational discretion to achieve their financial reporting objectives. For example, prior studies identify firms' low productivity (Kedia and Philippon [2009]), annual net losses (Roychowdhury [2006]), and CEOs' equity incentives (Wruck and Wu [2021]) as underlying drivers that lead to the firms' deteriorated accounting quality. Our paper highlights a bank's high NPL ratio as a key factor that affects the bank's subsequent reporting decision on its problem loans.

Similarly, Chopra, Subramanian, and Tantri (2021) show that less capitalized banks experience a larger reduction in lending and a higher increase in *zombie lending* in India. Peek and Rosengren (1995) highlight that troubled Japanese banks allocated more credit to impaired borrowers to avoid realization of losses on the banks' financial statements. Caballero, Hoshi, and Kashyap (2008) document that Japanese banks engaged in sham loan restructurings kept credit flow to insolvent borrowers. They further find that the *zombie lending* phenomenon had negative spillover effects on healthy firms' lending opportunities in Japan. We contribute to the literature by documenting that masking problem loans from financial statements due to banks' worsened asset quality may worsen the *zombie lending* phenomenon because borrowers of such hidden problem loans are expected to be insolvent. Our results show that high NPL ratio incentivizes banks to use their accounting discretion to under-report the size of their problem loans on their financial statements, which will ultimately help the growth of *zombie lending*.

2. Hypothesis Development

If a large number of bank borrowers face an event that will deteriorate their solvency status such as huge property damages by severe natural disasters, the bank's overall loan quality will be worsened. As documented by bank regulator's or many banks' internal guidelines, the bank needs to recognize and report additional problem loans such as nonperforming and non-accrual loans in its financial statement if those loans' quality is deemed to be indeed damaged.

Despite the clear guidelines, however, the classification of a loan into a troubled or a normal loan can be subject to the bank's discretion (Liu and Ryan [1995]; Liu and Ryan [2006]). First, the assessment of whether a past due loan is sufficiently well collateralized requires asset valuations.[10] Second, the classification of a debt under restructuring as a troubled or nontroubled

[10] Different types of loans may involve different levels of discretion to be classified as nonperforming loans. Compared to consumer loans, which are usually uncollateralized, commercial loans may involve managers' judgements to be classified as nonperforming

loan requires a business assessment. Because of the discretion available to banks in their NPL classifications, the changes in the banks' reported NPL amounts could be as untimely as those in their loan loss provisions (Liu and Ryan [1995]). An existing troubled loan with overdue payment of interest or principal may be rolled over or replaced with a new normal loan by loan renegotiation between banks and borrowers. The practices suggested above are examples of a bank's discretion, which can be used to curb the expansion of reported problem loans in its financial statement.

Our next question is when the bank will be incentivized to use its discretion to downsize the reported problem loans in its financial statement following the adverse shocks on the borrowers' overall solvency status. We conjecture that if the bank's existing asset quality prior to the shock was bad (for example, its NPL ratio is high), the further growth of the troubled loans following the shocks can be taken seriously by the market or its regulator as a bad signal for the bank's overall asset quality and riskiness. As documented in the literature, market participants discipline banks in response to their observed risk-taking behaviors by withdrawing deposits from the banks or by requiring higher deposit interest rates (e.g., Martinez Peria and Schmukler [2001]). A bank's growing problem loans may further trigger more stringent regulatory engagement.[11] If the bank manager has a serious concern about the market's disciplinary actions or regulatory interventions in response to the growing troubled loans reported on its financial statement, the manager may be highly incentivized to use the discretion available to them to under-report the size of its troubled loans on the books.

Using banks' discretion in classifying loans as NPLs is not the only way to deter the

loans because commercial loans are backed by collateral in many cases. While residential real estate loans strictly follow a past-due schedule to be classified as NPLs or charged off, assessments of commercial real estate loans are heterogeneous when they are judgmentally less collectible.

[11] According to "Guidance to banks on non-performing loans" (2017), the European Central Bank (ECB) requires banks with high NPL ratios to report their quantitative NPL targets and corresponding operational plans to national bank supervisors as well as the ECB. See details from here: https://www.bankingsupervision.europa.eu/ecb/pub/pdf/guidance_on_npl.en.pdf

expansion of their reported troubled loans. Banks may aggressively write off their existing toxic assets from their balance sheets. This strategy will directly downsize their troubled loans on the books. The charge-off, however, will lower the bank's existing loan loss reserve, which may require the bank to increase its loan loss provision. This ultimately deteriorates its profitability and reduces its equity capital. If the bank has a concern about negative responses from the market to its deteriorated profitability and capital buffer, the bank may less actively write off troubled loans from the books. Alternatively, the bank could also deter the expansion of additional troubled loans by shifting their loan portfolios toward safer assets. Banks may extend loans primarily to creditworthy borrowers and cut lending to low-quality borrowers who have higher potential to default in near future. The effect of changing a bank's loan portfolio, however, is not immediate because it takes time for even risky borrowers to make an overdue payment of interest or principal on their loans. Thus, the real management strategies described above are costly or ineffective in reducing the amount of troubled loans in a timely manner following negative shocks.

3. Empirical Methodology

This section outlines our empirical methodology. In this study, we examine whether banks with worse loan quality control the subsequent expansion of their reported problem loans when the banks face a negative shock on the borrowers' overall solvency status. For this test, we use natural disasters as shocks on local borrowers' solvency.[12] We employ an annual average of a bank's quarterly NPL ratios in the previous year as the variable that measures the bank's existing loan quality. The regression model is specified as follows.

[12] As reported in Table B.1 of the Appendix, we find that a local bank's delinquency rate tends to increase at a quarter-end following a natural disaster in the county where the local bank is located in the same quarter or its previous quarter. The results are stronger during periods with market stresses.

$$
\begin{aligned}
Y_{i,c,t} = \ & \alpha_0 + \alpha_1 Treated_{i,c} + \alpha_2 HighNPL_{i,c} + \alpha_3 Post_{i,t} + \alpha_4 Treated_{i,c} \\
& \cdot HighNPL_{i,c} + \alpha_5 HighNPL_{i,c} \cdot Post_{i,t} + \alpha_6 Treated_{i,c} \cdot Post_{i,t} \\
& + \alpha_7 Treated_{i,c} \cdot HighNPL_{i,c} \cdot Post_{i,t} + \Gamma X_{i,c,t} + FEs + \varepsilon_{i,c,t}
\end{aligned} \tag{1}
$$

The subscripts i, c, and t refer to bank, cohort, and year, respectively. We construct a two-year window with one for the pre-period prior to the natural disaster and one for the post-period with the shock. In these regressions, we employ a triple differences specification with three types of dummy variables. The first dummy is *Treated*, which equals 1 for the counties affected by natural disasters declared by FEMA in the post-period (t), and 0 otherwise. We omit counties that are damaged by natural disasters in two consecutive years (i.e., both pre- and post-periods). The control group (unaffected counties) does not experience any disaster in either pre- or post-periods. In these regressions, we limit samples to local banks to clearly identify the effect of each natural disaster on the local bank's problem loan reporting. Each local bank is assigned to one county where at least 65 percent of its total deposits are collected. [13] [14] [15] The second dummy is *HighNPL*, which takes a value of 1 if an annual average of the bank's quarterly NPL ratio as of the pre-period is higher than the median value for all banks in the same year, and 0 otherwise. Both *Treated* and *HighNPL* are time-invariant during the two-year window. The third one is *Post*, which identifies pre- and post-periods within the two-year event window.

For each disaster, we set a cohort identifier by pairing counties that are affected by disasters (treated county) and their adjacent counties that are unaffected by natural disasters (control county). Thus, local banks in treated counties and those in their adjacent control counties have the same cohort identifier in a two-year window (pre- and post-periods). A local bank with a high NPL ratio

[13] Our results are still consistent even when we use different cutoffs (for example, 75%, 85% or 95%) for the share of a bank's local deposits collected from its main county among its total deposits to define local banks.
[14] We find that local banks originate on average 62-65 percent of their total mortgages and small business loans to the assigned single county in each year in our sample.
[15] For non-local banks, large fractions of their loan portfolios are exposed to both the treated and control counties simultaneously due to their nationwide branch networks, which makes it hard to identify the effect of each disaster on the banks' reporting patterns of their problem loans. We can identify such reporting patterns only at each bank level, not at bank-county level.

is matched with another local bank with a low NPL ratio based on their total asset sizes. The matched control samples are selected from the same local areas (i.e., the same disaster county or adjacent unaffected counties in the same cohort).

In these regression, we employ a set of dependent variables ($Y_{i,c,t}$) related to the size of a bank's reported problem loans: *Ln(NPL)* and *Ln(non-accrual)*. *Ln(NPL)* is a natural log of an annual average of the bank's quarter-end total nonperforming loans in each year. *Ln(non-accrual)* is a natural log of an annual average of the bank's quarter-end total non-accrual loans in each year. The regressions add a set of control variables for bank characteristics ($Ln(total\ assets)$, $Ln(total\ deposits)$, BHC, $Capital$, $Leverage$, and ROA), which are included in $X_{i,c,t}$. Those control variables are set as of the pre-period and are time-invariant during the two-year event window. The interactions between the above control variables and *Post* are also included in $X_{i,c,t}$. Those variables control for the effect of banks' observable characteristics on their problem loan reporting in the subsequent year within the window.[16] Appendix A provides details of the variable definitions. In these regressions, we employ a set of fixed effect specifications: First, we employ *Bank-Cohort* and *Year-Cohort* fixed effects, which absorb any unobservable time-invariant bank-level characteristics across cohorts as well as time-specific factors for each of the pre- and post-periods.[17] In the second fixed effect specification, we replace *Year-Cohort* fixed effect with *Year-Cohort-HighNPL* fixed effect and compare banks' reporting behaviors only within the group of banks with similar NPL ratios in the same cohort. This fixed effect absorbs unobservable time-varying heterogeneity between the banks with high NPL ratios and those with low NPL ratios such as their risk appetites and corporate cultures during the two-year event window, which may affect

[16] Our results are robust to replacing time-invariant control variables within two-year window with time-varying ones.
[17] For example, Ng, Saffar, and Zhang (2020) document that banks' earnings management is closely related to political uncertainty in each period. The variation of political uncertainty of the US in each year is absorbed by *Year-Cohort* fixed effect in our setting.

their reporting patterns. Finally, we add *Year-County* fixed effect (in addition to *Bank-Cohort* and *Year-Cohort-HighNPL*) to absorb any remaining unobservable time-varying county-level characteristics, such as local credit demands and economic conditions. This fixed effect can mitigate the concern that differences in local credit demands following natural disasters between treated and control counties may lead to heterogeneity of local banks' problem loan reporting.

4. Data and Summary Statistics

4.1 Data sources

We construct a sample for banks' problem loan reporting from 2001 to 2019. For the main analysis, we compile data from several sources as described below.

Natural disasters: We obtain natural disaster data from the Federal Emergency Management Agency (FEMA). From this source, we can identify the counties experiencing natural disasters that are subject to emergency declarations made by the US president. Typical examples of natural disasters declared by FEMA include severe storms, floods, hurricanes, and wildfires.

Bank financial statements: Banks' financial statements are the main data sources for key dependent and independent variables. To identify banks with worse (*High NPL* = 1) or better (*High NPL* = 0) loan quality in the pre-period, we rely on the banks' balance sheet information and calculate the ratios of nonperforming loans over total loans at each quarter-end and take annual averages of those values. We construct our main dependent variables, such as the reported amounts of banks' nonperforming and non-accrual loans, as well as bank-level key control variables using banks' balance sheets and income statements. All of the banks' financial statements are available from Call Reports provided by the Federal Reserve Bank of Chicago and from Uniform Bank Performance Report provided by the Federal Financial Institutions Examination Council (FFIEC).

We obtain banks' quarterly liquidity creation data from Christa Bouwman's website.[18]

Local banks: We use deposit balances for each bank-branch level as of June 30th each year from the Summary of Deposit (SOD) provided by the Federal Deposit Insurance Corporation (FDIC) to identify local banks. Following Cortés (2014), we define local banks as the banks that collect at least 65 percent of their total deposits from a single county. We calculate each bank's county-year level local deposit volume using this data.

Mortgage origination: We obtain banks' mortgage origination in each county-year from the data provided by regulators (FFIEC) under the Home Mortgage Disclosure Act (HMDA). This data provides information for each mortgage lending activity, including the calendar years of the loan origination, the lenders that originated the mortgages, and the counties where the borrowers were located. The data also provides information on the purpose (e.g., refinancing or home purchase) or on the borrower type (e.g., high income or low income) of each mortgage loan. We aggregate the mortgage origination at bank-county-year level.

Small business lending: We rely on the data from the FFIEC to obtain information for small business loans originated by each bank in each county. From this data source, we can identify whether a loan is originated to a high- or low-income small businesses. We aggregate the small business loan origination at bank-county-year level.

4.2 Summary statistics

Table 1 presents summary statistics. The mean values of *Ln(NPL)* and *Ln(non-accrual)* are 6.4 and 5.9, respectively. Before taking the log transformation, banks hold an average of about $5.7 million in nonperforming loans and $4.1 million in non-accrual loans. About 29 percent of samples belong to the treated banks that face natural disasters. Exactly 50 percent of banks are

[18] The data for banks' liquidity creation are available at https://sites.google.com/a/tamu.edu/bouwman/data.

assigned to the group of banks with worse loan quality as indicated by their NPL ratios as of the pre-period. The mean values of log-transformed banks' total assets and total deposits are 12.0 and 11.8, respectively, which is \$0.7 billion and \$0.5 billion before the log transformation, respectively. Almost 79 percent of observations are affiliated to bank holding companies. Regulatory capital ratios are about 18 percent and leverage ratios are about 11 percent. Annualized returns on assets (ROA) is about 0.8 percent.

5. Empirical Results

5.1 Problem loan reporting of banks

This section discusses empirical results. First, we examine whether local banks with high NPL ratios as of the pre-period are less likely to increase the amounts of reported nonperforming or non-accrual loans in their financial statements following natural disasters in their regions.

In Table 2, we examine equation (1) using an annual average of the quarterly bank financial data for its problem loans. In Panel A, we report the subsequent change of the banks' annual average amount of their nonperforming loans from year *t*-1 to year *t* when the banks face natural disasters in their regions in year *t*. Columns (1) and (2) of Panel A report regression results for the banks with low NPL ratios (*HighNPL*=0) and the banks with high NPL ratios (*HighNPL*=1) as of year *t*-1. In Column (1), the coefficient for *Treated* × *Post* is positive, indicating that the reported nonperforming loans increase significantly following natural disasters in the regions of banks with low NPL ratios. In contrast, the coefficient for *Treated* × *Post* is negative but statistically insignificant in Column (2). This indicates that we cannot find any evidence that the banks with high NPL ratios report increasing amounts of nonperforming loans in their balance sheets after they experience negative shocks in their regions. In Column (3), we combine the samples used in Columns (1) and (2) and examine equation (1). The coefficient for the triple interaction term, *Treated* × *HighNPL* × *Post*, is significantly negative. This means that the banks with high NPL ratios are less likely to increase nonperforming loans in their financial statements following the shocks compared to the banks with low NPL ratios. It is important to note that *HighNPL* × *Post* is negative and significant in Column (3). This result implies that a bank with a high NPL ratio tends to reduce its reported NPLs even without any natural disaster shocks (in control regions); this can be interpreted as a mean-reverting process that high NPL banks control further expansion of their troubled loans and manage their asset quality in subsequent periods either through their internal risk management or due to regulatory interventions. From Columns (1) to (3), we employ *Bank-Cohort* and *Year-Cohort* fixed effects, which absorb all variation in *Treated*, *HighNPL*, *Post*, and *Treated* × *HighNPL*. Thus, we do not report those variables in the table. In Column (4), we interact the *HighNPL* dummy with existing *Year-Cohort* fixed effect as well as all other control variables to completely absorb the time-varying unobservable heterogeneity between the banks with high NPL ratios and those with low NPL ratios during the two-year event window such as their risk appetites, control systems, and regulatory scrutiny. The result is robust to employing the stricter specifications on fixed effects and control variables. In Column (4), *HighNPL* × *Post* is absorbed by the modified fixed effects. We continue to document a significantly negative coefficient for *Treated* × *HighNPL* × *Post*. Finally, in Column (5), we further add *Year-County* fixed effect to absorb any remaining unobservable time-varying county-level characteristics such as differences in local credit demands and local economic conditions across counties. As a result, *Treated* × *HighNPL* is dropped. Even with the additional fixed effect, our regression result for the triple interaction term (*Treated* × *HighNPL* × *Post*) remains consistent.

In Panel B, we examine the changes made to the banks' reported non-accrual loans when banks experience natural disasters in their regions. We document that regression results are similar to those of nonperforming loans in Panel A. In Column (1), the coefficient of *Treated* × *Post* is positive and significant. This shows that the banks with low NPL ratios are more likely to increase their non-accrual loans reported in their financial statements after facing natural disasters. On the contrary, in Column (2), the coefficient of *Treated* × *Post* is negative and insignificant. This shows that banks with high NPL ratios are more likely to under-report their non-accrual loan sizes after they face negative shocks. In Column (3), we combine the samples used in Columns (1) and (2). The triple interaction term of *Treated* × *HighNPL* × *Post* is negative and significant. This result highlights that expansion of the non-accrual loans reported in financial statements is smaller for the banks with high NPL ratios relative to those with low NPL ratios, given the natural disasters. In Column (4), we replace *Year-Cohort* fixed effect with *Year-Cohort-HighNPL* fixed effect and find that the result for the triple interaction term is consistent with that in Column (3). In Column (5), we add *Year-County* fixed effect to the regressions and find consistent results.

Collectively, we document that the banks that already have poor loan quality deter their expansion of problem loans after the banks experience negative shocks on their borrowers' overall solvency status.[19] [20]

In Figure 1, we examine dynamic effects of banks' existing loan quality on their subsequent problem loan reporting in a five-year window around natural disasters. Prior to natural disasters, we do not find any significant difference between high and low NPL banks in their problem loan reporting.[21] In the year of the shocks, however, the triple interaction terms become significantly

[19] If we convert annual data into quarterly frequency, high NPL banks' under-reporting patterns of their problem loans are the most significant in response to the local natural disasters happened in the treated county two quarters prior to the current quarter, as reported in Table B.2 of the Appendix.

[20] As a robustness, we limit samples to those in the treated counties. Consistent with the results in Table 2, the interaction terms of *HighNPL* × *Post* are negative and strongly significant as reported in Table B.3 of the Appendix. One caveat of these results is that the interaction term (*HighNPL* × *Post*) can capture general mean-reversion phenomena that high NPL banks tend to reduce their problem loans in subsequent periods even without any negative shocks on their asset quality.

[21] In this dynamic regressions, we decompose *Post* dummy into five different time dummy variables, *Shock (k),* where *k* ranges from -2 to +2. *Shock (k)* are a set of dummy variables that take a value of one if it is *k* years prior to (minus sign) or following (plus sign) the natural disasters, zero otherwise. Accordingly, the triple interaction term, *Treated* × *HighNPL* × *Post*, is replaced with

negative, meaning that high NPL banks tend to curb the expansion of their reported problem loans in financial statements compared to low NPL banks in response to natural disasters. In subsequent years, the triple interaction terms become insignificant again.[22]

5.2 Robustness tests

In this section, we conduct a set of robustness tests. First, we control for the potential confounding effects of banks' existing capital adequacy and profitability on their problem loan reporting. Banks' reporting of their problem loans may be affected by the banks' requirements to maintain their capital ratios above minimum levels or by their incentives to reserve a certain level of profitability rather than by the banks' tendency to manage their NPL ratios under their own designated thresholds (e.g., Beatty and Liao [2014]). If banks' problem loans and loan losses are expanded, their capital ratios are more likely to drop due to the expansion of risk-weighted assets as well as the decrease of equity capital. The increasing loan losses from the problem loans can worsen the banks' profitability as well. Thus, the banks with inadequate capital buffers or with lower profitability may have incentives to curb the expansion of their reported problem loans given the negative shocks on their asset quality. To mitigate the concern for those potential confounding effects, we add *LowCap*, which identifies the banks with an insufficient capital buffer (below median), and *LowROA*, which identifies the banks with return on assets (ROA) below the median value, as additional control variables. We further include interaction terms between each of those new variables (*LowCap* or *LowROA*) and each of the existing key independent variables (*Treated*, *PostShock*, and both) in the regressions as control variables. We expect that those sets of new variables control for potential confounding effects of the banks' incentives to maintain their capital buffers and profitability on their subsequent problem loan reporting. Table 3 reports the regression

five different interaction terms, $Treated \times HighNPL \times Shock(k)$. The year (-1) before the disaster is the omitted category.

[22] The regression results for the dynamics are reported in Table B.4 of the Appendix.

results. Even after adding these new sets of control variables, our main coefficients (*Treated* × *HighNPL* × *PostShock*) remain negative and statistically significant.

As a further robustness check, we conduct sub-sample regressions by sorting the banks by their capital adequacy or profitability. As reported in Table B.5 of the Appendix, we find that the high NPL banks tend to under-report their problem loans in their financial statements in response to local natural disasters even when the banks are better capitalized or highly profitable. These results imply that the under-reporting of problem loans is mainly driven by the banks' existing loan quality measured by their NPL ratios rather than by their less capital buffers or worsened profitability.

Second, to relieve a concern that the cutoff values (median) used to identify the banks with high/low NPL ratios are arbitrary, we replace the existing dummy variable (*HighNPL*) with quartile variables for banks' NPL ratios. Table B.6 in the Appendix reports the results. Panels A and B use the sizes of nonperforming loans and non-accrual loans as outcome variables, respectively. In this table, we define *NPLQ* as a quartile value for banks' average NPL ratios as of the pre-period and replace *HighNPL* with *NPLQ*. The values for the banks with the lowest average NPL ratios and the banks with the highest average NPL ratios as of the pre-period are 1 and 4, respectively. Even after we replace the dummy with quartile values, the results are robust. All triple interaction terms, *Treated* × *NPLQ* × *Post*, are negative and statistically significant in both panels.

Third, we run additional tests for banks' problem loan reporting by sorting samples to those with severe shocks and those with non-severe shocks. We expect that as local borrowers' solvency status is affected by natural disasters more severely, the local banks' asset quality is more heavily deteriorated, and thus the likelihood that banks with poor asset quality under-report their problem loans on the books will increase. To test this prediction, we employ monetary damages to properties by natural disasters to measure the severity of the natural disaster shocks.[23] If the county-aggregate monetary damages during a year scaled by its local population are above the median value, the treated county is assumed to face severe disasters. Otherwise, we assume that the treated county experiences non-severe disasters. As reported in Table B.7 in the Appendix, the under-reporting of problem loans by the banks with high NPL ratios following natural disasters is more significant when the banks are located in the treated counties with more severe disasters than those with less severe disasters.

Fourth, as documented in prior studies (for example, Miller, Moussawi, Wang, and Yang, 2021; Skała, 2021), banks' ownership or governance structures can affect their accounting management decisions. To mitigate the concern that our results might be driven by the variation of banks' ownership/governance structures, we run an additional robustness test by adding *Year-BHC* fixed effect. BHC is the identifier of the local bank's parent bank holding company. Our identifying assumption is that banks' ownership and governance structures are determined at the bank holding company and its affiliated local banks share the same level of ownership/governance structures. By adding *Year-BHC* fixed effect, we can absorb the variation of ownership/governance structures and any other remaining time-varying BHC-level unobservable characteristics that may affect banks' problem loan reporting behaviors. As reported in Table B.8 in the Appendix, our results remain consistent even after controlling for the effects of BHC-specific characteristics including the ownership and governance structures.[24]

Fifth, instead of the sizes of the problem loans, we use banks' NPL ratios as the outcome variable. For this test, we employ both the banks' year-end NPL ratios and the annual average of

[23] We obtain information on the monetary damage amounts by natural disasters from the Spatial Hazard Events and Losses Database for the United States.

[24] For this test, we limit samples to local banks, which are affiliated in a bank holding company with at least three subsidiary local banks in each year in our sample.

their quarter-end NPL ratios. As reported in Table B.9 in the Appendix, the results are consistent even when the sizes of banks' problem loans are replaced with their NPL ratios.

Finally, we sort samples to federally and state-chartered banks to investigate the differences in bank regulatory environments within the US are the main driver of the high NPL banks' under-reporting of their problem loans in response to natural disasters. As reported in Table B.10 in the Appendix, however, we find negative and significant results for triple interaction terms (*Treated* × *HighNPL* × *Post*) consistently in both federally and state-chartered banks.

5.3 Investigate alternative channels

In the previous sections, we document that banks with worse loan quality are more likely to control the expansion of their reported problem loans in balance sheets following negative shocks on their asset quality. We posit that those results are mainly driven by the use of accounting discretion given to banks' managers in recognizing and reporting their problem loans in financial statements. Alternatively, however, banks may choose other options to control the expansion of their reported problem loans. For example, banks may change their lending activities, i.e., shifting their credit portfolios toward high-quality borrowers instead of low-quality borrowers immediately after negative shocks. By expanding safer loans in new lending portfolios, banks may reduce the likelihood of further emergence of problem loans effectively in the near future. Our regression results in previous sections might be related to this channel. In this section, we test the alternative hypothesis (i.e., real loan management hypothesis) that the banks with poor loan quality tend to change their credit portfolios in response to negative shocks on their loan performance, which might subsequently help the banks to downsize their problem loans reported in financial statements.

In Table 4, we examine the above hypothesis by using the size of various types of mortgages (Panel A) and small business loans (Panel B) originated during a year in each county as the outcome variables ($Y_{i,c,t}$) in equation (1). In Column (1) of Panel A, we examine the size of total mortgages originated by each local bank in the county during the year. In Columns (2) and (3) of Panel A, we sort total mortgages to those for refinancing purposes and those for new home purchases.[25] In Columns (4) and (5) of Panel A, we further sort samples to mortgages to borrowers with annual gross income above and below \$50,000, respectively.[26] Because the credit risks may differ across loan types, the bank managers may shift their loan portfolios to loans with relatively less credit risks (i.e., refinanced mortgages and mortgages issued to borrowers with high income) following negative shocks. In contrast to the predictions above, our regression results show that the variable of our interest, *Treated* × *HighNPL* × *Post*, are insignificant in all columns, which means we cannot find any significant difference in loan portfolio changes across loan types between high NPL banks and low NPL banks within the two year window.

In Panel B, we examine changes in small business loan origination. Column (1) of Panel B reports aggregated small business loans originated by each local bank in a county during a year. In Columns (2) and (3) of Panel B, we sort the small business loans to large (above \$100,000) and small (below \$100,000) loans. Columns (4) and (5) of Panel B sort samples to loans to small businesses with annual revenues above and below \$1 million. Similar to the results in Panel A, the triple interaction terms, *Treated* × *HighNPL* × *Post*, are statistically insignificant in all columns, suggesting that banks with high NPL ratios do not change their small business lending patterns across types relative to those with low NPL ratios in response to natural disasters. In short, the regression results in Tables 2 and 3, which highlight a significant control on expansion of reported

[25] When a loan is refinanced to an existing borrower, the bank can more easily identify the borrower's credit quality by using its accumulated borrower-specific information such as the borrower's repayment records. In contrast, when the loan is issued for new home purchase purpose, the bank needs to rely mainly on limited hard information such as collateral value and credit score without past transaction records. Thus, uncertainties on the borrowers' solvency status and credit risks may be greater for the loans for new home purchases than for those for refinancing purposes if other conditions are equal.

[26] One may conjecture that mortgage loans to the borrowers with higher income are relatively safer than those to the borrowers with lower income if other conditions are identical.

problem loans by the bank with high NPL ratio following negative shocks is not supported by the notion that changes in problem loans are potentially driven by changes in operational decisions to shift their loan portfolios to safer loans. This may be because a dramatic change of loan compositions across loan types (within a two-year window) perhaps severely affects the banks' current customer bases, revenues, and profits while the effects on the size of their problem loans are unclear, at least in the short term.

In Table 5, we further examine the changes made to banks' balance sheet structures within a two-year window with the same regression specifications described in equation (1). For this test, we employ eight outcome variables related to banks' balance sheet structures that may be affected by lending activities: total assets (*Ln(assets)*), total loans (*Ln(loans)*), total credits (*Ln(credits)*), total loans over total assets (*Loans/assets*), total liquid assets over total assets (*Liquid/assets*), total credits over total assets (*Credits/assets*), real estate loans over total loans (*Estate/loans*), and commercial and industrial loans over total loans (*C&I/loans*). In our study, *Credits* is defined as the sum of total loans and unused commitments in the off-balance sheet. All those variables are an annual average of quarter-end values. In all regressions, the coefficients for the triple interaction terms, *Treated* × *HighNPL* × *Post,* are again statistically insignificant. Such insignificant results imply that a bank's real management that accompanies its asset structure changes is not the driver behind under-reporting of problem loans for the high-NPL bank following negative shocks.

In Table 6, we further investigate whether a change in high NPL banks' liquidity creation following the shocks can be a source of the banks' reduced problem loan size in their financial statements. For this test, we employ the liquidity creation variables developed by Berger and Bouwman (2009). We use four liquidity creation measures (total, asset-side, liability-side, and off-balance sheet side) and do not document statistically significant results for the triple interaction terms, *Treated* × *HighNPL* × *Post*. In other words, the liquidity amounts created by the high NPL banks do not significantly change in response to the natural disasters compared to those by the low NPL banks within the two-year event window.

Another real management method potentially adopted to control the expansion of reported problem loans is to aggressively write off the banks' toxic assets. To test this possibility, we use the size of loan charge-offs during a year as the outcome variable in equation (1). All other regression settings are the same as equation (1). The results are presented in Table 7. The triple interaction terms, *Treated* × *HighNPL* × *Post*, are negative in all columns although those are statistically insignificant. These results indicate that the banks with high NPL ratios are less likely to increase the amount of loan charge-offs than the banks with high NPL ratios following natural disasters. In other words, banks with high NPL ratios do not use the loan charge-off to curb the expansion of the reported problem loans following negative shocks.[27] [28]

Overall, we reject the hypothesis that banks with high NPL ratios manage the amount of their reported nonperforming and non-accrual loans by shifting their credit portfolios toward high-quality borrowers from low-quality ones or by writing off more toxic assets from the books in response to negative shocks on their asset quality.

5.4 Long term consequences

In previous sections, we focus on short-term effects of banks' existing loan quality on their problem loan reporting given natural disasters in the regions in two-year window (one for the pre-

[27] The banks with worse loan quality may not increase charge-off in response to borrowers' solvency shock because the charge-off will lead to a negative effect on their profitability and equity capital via additional loan losses after the charge-off. In Table B.11 in the Appendix, we report the positive effect of a bank's charge-off on its loan loss provision and its negative effect on its net incomes as well as its leverage ratio (tier 1 capital over total assets).
[28] Under-reporting of problem loans by banks with high NPL ratios following natural disasters may be the reason for the reduced amount of the banks' charge-off in the post-period. In untabulated results, we find a significant positive correlation between the size of nonperforming loans at each quarter-end and that of charge-off during the same or the following quarter.

period and one for the post-period). Now, we move to their longer-term consequences by extending the event window to four years (one for the pre-period and its following three years for the post-period). Similar to our baseline regressions, we keep two observations per bank in each cohort by collapsing post periods (three years) into one observation. The results are reported in Panel A of Table 8. Interestingly, in these longer term event windows, the triple interaction terms, *Treated* × *HighNPL* × *Post*, become insignificant. This means that the high NPL banks' under-reporting pattern is significant in the short-term but weaker in its subsequent years.

We further examine the longer-term effects on the high NPL banks' balance sheet structures. In previous tests with two-year window, we could not find any significant changes made to high NPL banks' balance sheet structures relative to those of low NPL banks following natural disasters. In contrast, if we add subsequent two more years to the event window, we find significant changes to high NPL banks' balance sheet structures in the extended post period. As reported in Panel B of Table 8, high NPL banks are more likely to expand liquid assets proportion instead of loans among asset portfolios than low NPL banks do. High NPL banks also make a significant reduction to liquidity creation from their off-balance sheet items.

From the set of short- and long-term results, we conclude that high NPL banks tend to use their accounting discretion to under-report their problem loans only in the short-term in response to negative shocks on their asset quality. In the long run, however, those high NPL banks are more likely to downsize their credit and liquidity supply. These consequences may result from high NPL banks' long-run real management to control the size of potential troubled loans in the future.

5.5 Loan quality and deposit funding

In this section, we examine the reasons underlying the bank managers' motivation to under-report their problem loans following negative shocks on borrowers' solvency status if the banks'

NPL ratios were high before the shock. We posit that the high NPL ratio can be regarded as a bad signal for the bank's existing asset quality by its stakeholders including depositors and regulators.[29] To verify this prediction, we focus on how depositors respond to banks' asset quality. We relate a bank's existing NPL ratio as of the pre-period to changes in the bank's local deposit volume in its county within the two-year window. The regression results are reported in Table 9. We see that the local banks with high NPL ratios as of the pre-period are more likely to face a reduction of their local deposits in the county in the post-period. Banks in both the treated and the control counties experience a significant reduction of their county-aggregate deposits in the post-period if their NPL ratios were high in the pre-period. These results highlight that the local deposit markets indeed adversely respond to banks' existing high NPL ratios.

In Table 10, we repeat the deposit analyses after sorting samples to different sets of sub-groups. In Panel A, we compare the periods of market stress and those of non-stress. The market stress is measured by an annual average of monthly spreads between 3-month Commercial Paper (CP) rate and 3-month T-bill rate following the approach of Acharya and Mora (2015). If the average spread is above the median, the period is defined as a market with stress. As reported in Panel A, the significant negative effect of a bank's high NPL ratio on its local deposits is observed only during the market stress period. This may be because the market's concern for a bank's deteriorated asset quality will be more serious during the market downturn than under normal market conditions. In Panel B, we sort samples to the local banks in competitive markets and those in concentrated markets. Market competitiveness is measured by the deposit market Herfindahl-Hirschman Index (HHI) in each county. If the HHI is below the median, the county is defined as a

[29] One example of such regulatory engagements for banks' growing problem loans is to require banks with high NPL ratios to report their quantitative NPL targets and their corresponding operational plans to national bank supervisors. This requirement is documented in "Guidance to banks on non-performing loans" (2017) for European banks. See details from here: https://www.bankingsupervision.europa.eu/ecb/pub/pdf/guidance_on_npl.en.pdf

competitive market. The results show that the negative relationship between banks' NPL ratios and their local deposits is observed only in the competitive markets. Those results imply that if the market competition is high, the market's negative response to a bank's worse asset quality becomes more serious and the bank loses its deposits more severely. Finally, in Panel C, we compare the counties with a large number of banks and those with a small number of banks scaled by their local populations. If the number of bank brands in a county, scaled by its population, is below the median, the county is defined as a market with fewer banks. As reported in Panel C, if the number of banks is less, the results are stronger. In other words, if the number of banks in the region is small relative to its population, the asset quality of individual local banks is more easily observable to local market participants. This may drive stronger responses by market participants to local banks' bad asset quality in those regions in terms of their deposits.

If a bank manager is well aware of the possibility that such depositors' disciplinary actions against the bank's worse asset quality are more severe under market stress, in competitive markets, and in markets with fewer banks, the bank manager's incentive to under-report the problem loans following negative shocks may be more significant in those environments. As the final step, we test those predictions by moving back to our baseline regressions for reported problem loans after sorting samples to such three pairs of sub-groups. Except for the sample coverage, all other regression specifications are the same as in equation (1). The regressions results are reported in Table 11. In Panel A, we compare the results in stress and those in non-stress periods. In Panel B, we sort samples into those in competitive and concentrated markets. In Panel C, we compare the regions with more banks and those with less banks. Similar to the results reported in Table 10, the high-NPL banks' under-reporting pattern of their problem loans following natural disasters is stronger during market stress periods, in competitive markets, and in counties with fewer banks.

From the sets of regression results reported in Tables 9 to 11, we conclude that the market's adverse response (i.e., deposit drawdown) to the bank's expanding problem loans may be one of the main reasons underlying bank managers' strong incentives to under-report problem loans in financial statements following negative shocks on their asset quality.

6. Conclusion

In this study, we examine the effect of banks' existing loan quality measured by NPL ratios on their subsequent problem loan reporting in their financial statements following a natural disaster, which is employed as a negative shock on local borrowers' overall solvency status. If banks' NPL ratios are sufficiently high, those banks are less likely to increase their reported problem loans (nonperforming or non-accrual loans) on their balance sheets relative to those with lower NPL ratios. Our results are robust to controlling for the effects of banks' existing capital adequacy and profitability on their problem loan reporting. Further evidence shows that the control of reported problem loans is achieved mainly by using accounting discretion available to the bank managers rather than transforming their loan portfolios toward safer loans or writing off more toxic assets from the books. We document that the results are stronger under the situations in which local depositors are more responsive to the banks' worse asset quality such as during market stress periods, in competitive local markets, and with fewer banks relative to population in the local market.

We conclude by highlighting that banks do care about their NPL ratios, and their existing NPL ratios are an important driver that differentiates the strictness of the banks' current problem loan reporting by affecting the bank managers' incentive to control the size of its reported problem loans. This incentive can be a source of the growth in *zombie lending* (hidden loans provided to insolvent borrowers) by banks.

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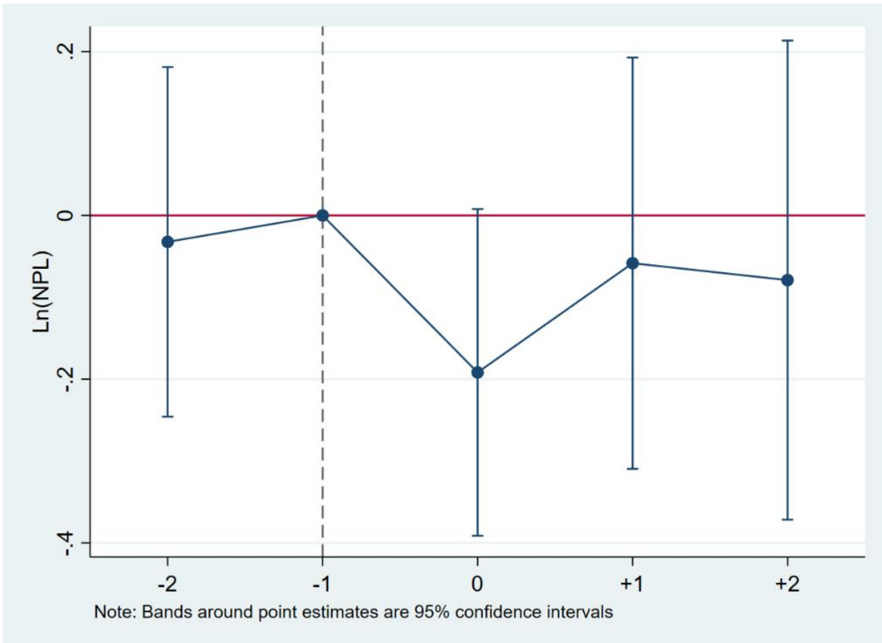
Figure 1: Dynamics of loan quality and problem loan reporting around natural disasters

The graph plots the point estimates and 95% confidence intervals of the coefficients for the triple interaction term, *Treated* × *HighNPL* × *Shock(k)*, where *k* ranges from -2 to +2. The year (-1) before the disaster is the omitted category. The dependent variable is *Ln(NPL)* in Panel (a) and *Ln(non-accrual)* in Panel (b).

a. Ln(NPL)



b. Ln(non-accrual)

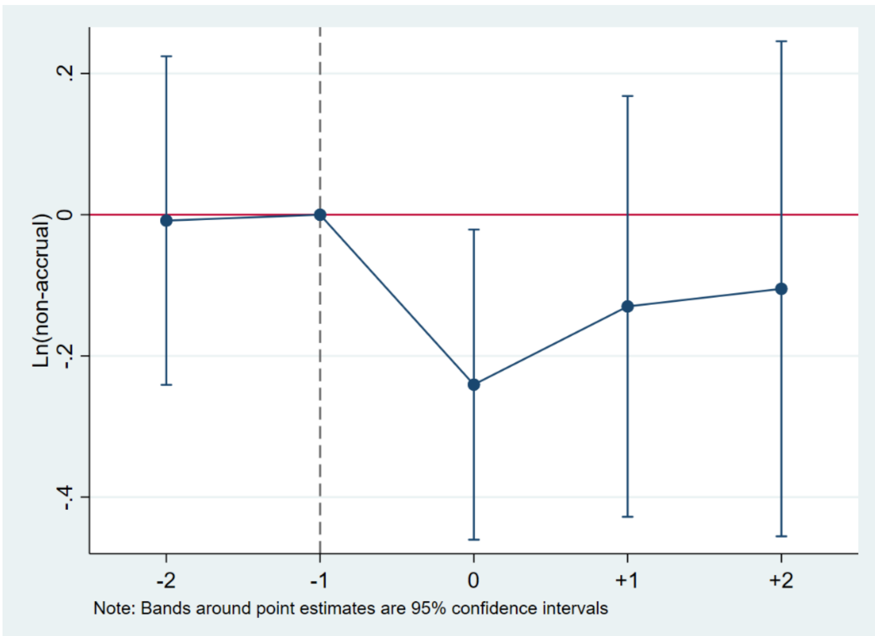


Table 1: Summary statistics

This table reports summary statistics for key dependent and independent variables. The sample period is from 2001 to 2019. Variable definitions are provided in Appendix A.

				Percentile Distribution		
	N	Mean	S.D.	25th	Median	75th
Ln(NPL)	35200	6.409	2.283	5.449	6.688	7.795
Ln(non-accrual)	35200	5.904	2.669	4.808	6.441	7.644
Treated	35200	0.288	0.453	0.000	0.000	1.000
Post	35200	0.500	0.500	0.000	0.500	1.000
HighNPL	35200	0.500	0.500	0.000	0.500	1.000
LowCap	35200	0.515	0.500	0.000	1.000	1.000
LowROA	35200	0.503	0.500	0.000	1.000	1.000
Ln(total assets)	35200	11.992	1.177	11.251	11.896	12.628
Ln(total deposits)	35200	11.772	1.201	11.053	11.709	12.427
BHC	35200	0.793	0.405	1.000	1.000	1.000
Capital	35200	18.300	81.483	11.747	14.506	18.724
Leverage	35200	11.043	6.431	8.457	9.780	11.862
ROA	35200	0.805	3.206	0.423	0.820	1.239

Table 2: Bank loan quality and problem loan reporting

This table examines the effect of banks' existing loan quality (NPL ratios) on subsequent reporting of their problem loans (nonperforming or non-accrual loans) given natural disasters in the counties where local banks are located. The sample consists of two-year event windows (one year for the pre-period and one year for the post-period) from 2001 to 2019 for each bank. In Panel A, *Ln(NPL)* is a natural log of an annual average of a bank's quarter-end nonperforming loans. In Panel B, *Ln(non-Accrual)* is a natural log of an annual average of a bank's quarter-end non-accrual loans. *HighNPL* takes a value of 1 if an annual average of a bank's quarter-end NPL ratio is higher than the median value of all banks in the same year as of the pre-period, 0 otherwise. *Treated* is a treatment dummy that takes a value of 1 for counties that experience at least one natural disaster in the post-period and no disaster in the pre-period. *Treated* takes a value of 0 for counties that experience no natural disasters in both pre- and post-periods and are adjacent to the counties with the severe natural disasters. A cohort identifier is assigned to observations in each treated and control pair. *Post* takes a value of 1 in the post-period, 0 in the pre-period. A local bank with *HighNPL* = 1 is matched with a local bank with *HighNPL* = 0 that is closest in terms of total assets. The regression also includes a set of control variables for bank characteristics ($Ln(total\ assets)$, $Ln(total\ deposits)$, BHC, $Capital,\ Leverage,$ and ROA). Interactions between each of the above controls and the *Post* dummy are also included as control variables. The values of those control variables are fixed as of the year-end of the pre-period within the cohort. The coefficients on these variables are not reported for compactness. Standard errors are clustered at the bank-level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. *t*-statistics are in parentheses. Variable definitions are provided in Appendix A.

Panel A	Ln(NPL)				
	LowNPL	HighNPL	Both	Both	Both
	(1)	(2)	(3)	(4)	(5)
Treated × Post	0.225**	-0.025	0.222***	0.225**	
	(2.50)	(-0.89)	(2.87)	(2.50)	
HighNPL × Post			-0.439***		
			(-10.42)		
Treated × HighNPL × Post			-0.236***	-0.251***	-0.255***
			(-3.24)	(-2.65)	(-2.77)
Observations	17600	17600	35200	35200	35200
Adjusted R^2	0.865	0.833	0.878	0.887	0.877
Bank Controls	Y	Y	Y	Y	Y
Bank-Cohort FE	Y	Y	Y	Y	Y
Year-Cohort FE	Y	Y	Y	N	N
Year-Cohort-HighNPL FE	N	N	N	Y	Y
Year-County FE	N	N	N	N	Y

Panel B	Ln(non-accrual)				
	LowNPL	HighNPL	Both	Both	Both
	(1)	(2)	(3)	(4)	(5)
Treated × Post	0.271***	-0.022	0.267***	0.271***	
	(2.83)	(-0.64)	(3.17)	(2.83)	
HighNPL × Post			-0.439***		
			(-9.04)		
Treated × HighNPL × Post			-0.277***	-0.294***	-0.254**
			(-3.34)	(-2.88)	(-2.54)
Observations	17600	17600	35200	35200	35200
Adjusted R^2	0.876	0.816	0.879	0.887	0.878
Bank Controls	Y	Y	Y	Y	Y
Bank-Cohort FE	Y	Y	Y	Y	Y
Year-Cohort FE	Y	Y	Y	N	N
Year-Cohort-HighNPL FE	N	N	N	Y	Y
Year-County FE	N	N	N	N	Y

Table 3: Bank loan quality and problem loan reporting (Control for bank capital adequacy and profitability)

This table examines the effect of banks' existing loan quality (NPL ratios) on subsequent reporting of their problem loans (nonperforming or non-accrual loans) given natural disasters in the counties where local banks are located after controlling for banks' capital adequacy and profitability. The sample consists of two-year event windows (one year for the pre-period and one year for the post-period) from 2001 to 2019 for each bank. We add control variables related to banks' capital ratios (*LowCap*) and their interactions with key independent variables as well as those related to banks' profitability (*LowROA*) and their interactions with other key independent variables in addition to existing control variables. *LowCap* is a dummy variable that takes a value of 1 if the bank's annual average capital ratio is below the median of all banks of the same year as of the pre-period, 0 otherwise. *LowROA* is a dummy variable that takes a value of 1 if the bank's return on assets (ROA) is below the median as of the pre-period, 0 otherwise. The regression also includes a set of control variables for bank characteristics listed in Table 2. The coefficients on these variables are not reported for compactness. All other regression specifications are the same as those in Table 2. Standard errors are clustered at the bank-level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. *t*-statistics are in parentheses. Variable definitions are provided in Appendix A.

	Ln(NPL)			Ln(non-accrual)		
	(1)	(2)	(3)	(4)	(5)	(6)
Treated × Post	0.270***	0.239**		0.340***	0.297***	
	(3.18)	(2.50)		(3.53)	(2.79)	
HighNPL × Post	-0.445***			-0.447***		
	(-10.47)			(-9.06)		
Treated × HighNPL × Post	-0.228***	-0.251***	-0.246***	-0.267***	-0.294***	-0.247**
	(-3.06)	(-2.60)	(-2.64)	(-3.13)	(-2.82)	(-2.43)
LowCap × Post	0.051	0.036	0.067	0.072	0.048	0.060
	(1.11)	(0.68)	(1.00)	(1.29)	(0.75)	(0.72)
Treated × LowCap × Post	-0.105	-0.085	-0.133	-0.209**	-0.164*	-0.227*
	(-1.29)	(-0.97)	(-1.22)	(-2.32)	(-1.70)	(-1.87)
LowROA × Post	0.028	-0.014	-0.031	0.030	-0.031	-0.049
	(0.59)	(-0.25)	(-0.41)	(0.54)	(-0.48)	(-0.56)
Treated × LowROA × Post	0.007	0.061	0.025	0.061	0.121	0.115
	(0.09)	(0.69)	(0.22)	(0.68)	(1.19)	(0.88)
Observations	35200	35200	35200	35200	35200	35200
Adjusted R^2	0.878	0.887	0.877	0.879	0.887	0.878
Bank Controls	Y	Y	Y	Y	Y	Y
Bank-Cohort FE	Y	Y	Y	Y	Y	Y
Year-Cohort FE	Y	N	N	Y	N	N
Year-Cohort-HighNPL FE	N	Y	Y	N	Y	Y
Year-County FE	N	N	Y	N	N	Y

Table 4: Bank loan quality and lending activity

This table examines the effect of banks' existing loan quality (NPL ratios) on subsequent loan origination (mortgage and small business loans) given natural disasters in the counties where local banks are located. The sample consists of two-year event windows (one year for the pre-period and one year for the post-period) for each bank from 2001 to 2016 for mortgages and from 2001 to 2018 for small business lending. *Ln(mortgage)* is a natural log of a bank's county-aggregate mortgage origination in a year. *Ln(refine mortgage)* is a natural log of a bank's county-aggregate mortgages originated for refinancing purposes in a year. *Ln(home mortgage)* is a natural log of a bank's county-aggregate mortgages originated for new home purchases in a year. *Ln(high income mortgage)* is a natural log of a bank's county-aggregate mortgages originated to borrowers with annual gross income above $50,000 during a year. *Ln(low income mortgage)* is a natural log of a bank's county-aggregate mortgages originated to borrowers with annual gross income below $50,000 during a year. *Ln(SBL)* is a natural log of a bank's county-aggregate small business loan origination in a year. *Ln(large SBL)* is a natural log of a bank's county-aggregate small business loan origination with a loan size above $100,000 during a year. *Ln(small SBL)* is a natural log of a bank's county-aggregate small business loan origination with a loan size below $100,000 during a year. *Ln(high income SBL)* is a natural log of a bank's county-aggregate loans originated to small businesses with annual revenues higher than $1 million in a year. *Ln(low income SBL)* is a natural log of a bank's county-aggregate loans originated to small businesses with annual revenues lower than $1 million in a year. The regression also includes a set of control variables for bank characteristics listed in Table 2. The coefficients on these variables are not reported for compactness. All other regression specifications are the same as those in Table 2. Standard errors are clustered at the bank-level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. *t*-statistics are in parentheses. Variable definitions are provided in Appendix A.

Panel A	Ln(mortgage)	Ln(refin mortgage)	Ln(home mortgage)	Ln(high income mortgage)	Ln(low income mortgage)
	(1)	(2)	(3)	(4)	(5)
Treated × HighNPL× Post	-0.040	0.225	-0.059	-0.076	-0.138
	(-0.27)	(0.94)	(-0.24)	(-0.33)	(-0.51)
Observations	16494	16494	16494	16494	16494
Adjusted R^2	0.808	0.695	0.677	0.758	0.796
Bank Controls	Y	Y	Y	Y	Y
Bank-Cohort FE	Y	Y	Y	Y	Y
Year-Cohort-HighNPL FE	Y	Y	Y	Y	Y
Year-County FE	Y	Y	Y	Y	Y

Panel B	Ln(SBL)	Ln(large SBL)	Ln(small SBL)	Ln(high income SBL)	Ln(low income SBL)
	(1)	(2)	(3)	(4)	(5)
Treated × HighNPL× Post	-0.613	-1.012	0.233	-0.647	0.282
	(-1.60)	(-1.31)	(0.47)	(-0.67)	(0.46)
Observations	2940	2940	2940	2940	2940
Adjusted R^2	0.887	0.895	0.764	0.687	0.815
Bank Controls	Y	Y	Y	Y	Y
Bank-Cohort FE	Y	Y	Y	Y	Y
Year-Cohort-HighNPL FE	Y	Y	Y	Y	Y
Year-County FE	Y	Y	Y	Y	Y

Table 5: Bank loan quality and balance sheet structure

This table examines the effect of banks' existing loan quality (NPL ratios) on subsequent balance sheet structures given natural disasters in the counties where local banks are located. The sample consists of two-year event windows (one year for the pre-period and one year for the post-period) from 2001 to 2019 for each bank. We employ eight different outcome variables related to banks' balance sheet structures: *Ln(assets), Ln(loans), Ln(credits), Loans/assets, Liquid/assets, Credits/assets, Estate/loans,* and *C&I/loans*. *Ln(assets)* is a natural log of an annual average of a bank's quarter-end total assets. *Ln(loans)* is a natural log of an annual average of a bank's quarter-end total loans. *Ln(credits)* is a natural log of an annual average of a bank's quarter-end total credit. Total credit is defined as sum of total loans and unused loan commitments in the off-balance sheet. *Loans/assets* is an annual average of quarter-end ratios of a bank's total loans over total assets (percentage). *Liquid/assets* is an annual average of quarter-end ratios of a bank's liquid assets over total assets (percentage). Liquid assets are defined as the sum of cash and securities. *Credits/assets* is an annual average of quarter-end ratios of a bank's total credits over total assets (percentage). *Estate/loans* is an annual average of quarter-end ratios of a bank's real estate loans over total loans (percentage). *C&I/loans is a*n annual average of quarter-end ratios of a bank's commercial and industrial loans over total loans (percentage). The regression also includes a set of control variables for bank characteristics listed in Table 2. The coefficients on these variables are not reported for compactness. All other regression specifications are the same as those in Table 2. Standard errors are clustered at the bank-level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. *t*-statistics are in parentheses. Variable definitions are provided in Appendix A.

Panel A	Ln(assets)	Ln(loans)	Ln(credits)	Loans/assets
	(1)	(2)	(3)	(4)
Treated × HighNPL × Post	-0.001	-0.003	-0.008	-0.130
	(-0.13)	(-0.34)	(-0.73)	(-0.43)
Observations	35200	35200	35200	35200
Adjusted R^2	0.996	0.993	0.987	0.961
Bank Controls	Y	Y	Y	Y
Bank-Cohort FE	Y	Y	Y	Y
Year-Cohort-HighNPL FE	Y	Y	Y	Y
Year-County FE	Y	Y	Y	Y

Panel B	Liquid/assets	Credits/assets	Estate/loans	C&I/loans
	(5)	(6)	(7)	(8)
Treated × HighNPL × Post	-0.096	-1.501	-0.022	0.071
	(-0.31)	(-0.64)	(-0.09)	(0.27)
Observations	35200	35200	35083	35083
Adjusted R^2	0.959	0.908	0.985	0.950
Bank Controls	Y	Y	Y	Y
Bank-Cohort FE	Y	Y	Y	Y
Year-Cohort-HighNPL FE	Y	Y	Y	Y
Year-County FE	Y	Y	Y	Y

Table 6: Bank loan quality and liquidity creation

This table examines the effect of banks' existing loan quality (NPL ratios) on their subsequent liquidity creation given natural disasters in the counties where local banks are located. *LiquidityCreation* is Berger and Bouwman's (2009) liquidity creation measure for each bank (total, asset-side, liability-side, or off-balance sheet side in Columns 1–4, respectively). Original quarter-end values are collapsed into their annual averages for each bank. The sample consists of two-year event windows (one year for the pre-period and one year for the post-period) from 2001 to 2016 for each bank. The regression also includes a set of control variables for bank characteristics listed in Table 2. The coefficients on these variables are not reported for compactness. All other regression specifications are the same as those in Table 2. Standard errors are clustered at the bank-level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. *t*-statistics are in parentheses. Variable definitions are provided in Appendix A.

	LiquidityCreation			
	Total	Asset-side	Liability-side	OBS-side
	(1)	(2)	(3)	(4)
Treated × HighNPL × Post	-0.000	-0.001	0.001	-0.000
	(-0.01)	(-0.43)	(0.65)	(-0.00)
Observations	26890	26890	26890	26890
Adjusted R^2	0.758	0.969	0.960	0.672
Bank Controls	Y	Y	Y	Y
Bank-Cohort FE	Y	Y	Y	Y
Year-Cohort-HighNPL FE	Y	Y	Y	Y
Year-County FE	Y	Y	Y	Y

Table 7: Bank loan quality and loan charge-off

This table examines the effect of banks' existing loan quality (NPL ratios) on subsequent loan charge-off given natural disasters in the counties where local banks are located. The sample consists of two-year event windows (one year for the pre-period and one year for the post-period) from 2001 to 2019 for each bank. *Ln(Charge-off)* is a natural log of total amount of loan charge-off during a year. The regression also includes a set of control variables for bank characteristics listed in Table 2. The coefficients on these variables are not reported for compactness. All other regression specifications are the same as those in Table 2. Standard errors are clustered at the bank-level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. *t*-statistics are in parentheses. Variable definitions are provided in Appendix A.

	Ln(Charge-off)		
	(1)	(2)	(3)
Treated × Post	0.115	0.111	
	(1.48)	(1.22)	
HighNPL × Post	-0.202***		
	(-3.56)		
Treated × HighNPL × Post	-0.091	-0.083	-0.090
	(-1.10)	(-0.77)	(-0.84)
Observations	35200	35200	35200
Adjusted R^2	0.807	0.802	0.777
Bank Controls	Y	Y	Y
Bank-Cohort FE	Y	Y	Y
Year-Cohort FE	Y	N	N
Year-Cohort-HighNPL FE	N	Y	Y
Year-County FE	N	N	Y

Table 8: Long-term effects on problem loan reporting and balance sheet structures

This table examines the long-term average effects of banks' existing loan quality (NPL ratios) on subsequent reporting of their problem loans (nonperforming or non-accrual loans, Panel A) and key balance sheet structures (Panel B) given natural disasters in the counties where local banks are located. The sample consists of four-year event windows (one year for the pre-period and three years for the post-period) from 2001 to 2019 for each bank. The observations in the post-period (three-years) are collapsed into one observation for each bank in the cohort. The regression also includes a set of control variables for bank characteristics listed in Table 2. The coefficients on these variables are not reported for compactness. All other regression specifications are the same as those in Table 2. Standard errors are clustered at the bank-level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. *t*-statistics are in parentheses. Variable definitions are provided in Appendix A.

Panel A	Ln(NPL)	Ln(non-accrual)
	(1)	(2)
Treated × HighNPL × Post	-0.179	-0.078
	(-1.37)	(-0.52)
Observations	23072	23072
Adjusted R^2	0.859	0.847
Bank Controls	Y	Y
Bank-Cohort FE	Y	Y
Year-Cohort-HighNPL FE	Y	Y
Year-County FE	Y	Y

Panel B	Loans/assets	Liquid/assets	Credits/assets	LiquidityCreation (OBS-side)
	(1)	(2)	(3)	(4)
Treated × HighNPL × Post	-0.694**	0.670**	-0.875*	-0.003**
	(-2.51)	(2.46)	(-1.76)	(-2.34)
Observations	23072	23072	23072	21884
Adjusted R^2	0.995	0.978	0.999	0.988
Bank Controls	Y	Y	Y	Y
Bank-Cohort FE	Y	Y	Y	Y
Year-Cohort-HighNPL FE	Y	Y	Y	Y
Year-County FE	Y	Y	Y	Y

Table 9: Bank loan quality and local deposits

This table examines the effect of banks' existing loan quality (NPL ratios) on subsequent local deposits in the counties where local banks are located. The sample consists of two-year event windows (one year for the pre-period and one year for the post-period) from 2001 to 2019 for each bank. *Ln(Local deposits)* is a natural log of a bank's county-aggregate deposits as of June 30 of each year in the county where at least 65 percent of the bank's total deposits are collected. Column (1) covers entire samples. Columns (2) and (3) limit samples to the banks in the treated counties and those in control counties, respectively. The regression also includes a set of control variables for bank characteristics listed in Table 2. The coefficients on these variables are not reported for compactness. All other regression specifications are the same as those in Table 2. Standard errors are clustered at the bank-level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. *t*-statistics are in parentheses. Variable definitions are provided in Appendix A.

	Ln(Local deposits)		
	All counties	Treated counties	Control counties
	(1)	(2)	(3)
HighNPL × Post	-0.042***	-0.040***	-0.045**
	(-3.21)	(-2.62)	(-2.35)
Observations	35108	10112	24996
Adjusted R^2	0.943	0.935	0.946
Bank Controls	Y	Y	Y
Bank-Cohort FE	Y	Y	Y
Year-Cohort FE	Y	Y	Y
Year-County FE	Y	Y	Y

Table 10: Bank loan quality and local deposits
(Sort samples by business environments)

This table examines the effect of banks' existing loan quality (NPL ratios) on the banks' subsequent local deposits in the counties where local banks are located. The sample consists of two-year event windows (one year for the pre-period and one year for the post-period) from 2001 to 2019 for each bank. *Ln(Local deposits)* is a natural log of a bank's county-aggregate deposits as of June 30 of each year in the county where at least 65 percent of the bank's total deposits are collected. We further sort samples to those in market stress and non-stress periods (Panel A), those in competitive and concentrated counties (Panel B), or those in counties with greater and smaller numbers of banks (Panel C). A market stress is measured by an annual average of monthly spreads between 3-month Commercial Paper (CP) rate and 3-month T-bill rate. If the average spread is above the median, the period is defined as a market stress in Panel A. Market competitiveness is measured by the deposit market Herfindahl-Hirschman Index (HHI) in each county. If the HHI is below the median, the county is defined as a competitive market in Panel B. Finally, if the number of bank brands in a county, scaled by its population, is below the median, the county is defined as a market with less banks in Panel C. The regression also includes a set of control variables for bank characteristics listed in Table 2. The coefficients on these variables are not reported for compactness. All other regression specifications are the same as those in Table 2. Standard errors are clustered at the bank-level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. *t*-statistics are in parentheses. Variable definitions are provided in Appendix A.

Panel A: Stress vs. non-stress	Ln(Local deposits)	
	Stress	Non-stress
HighNPL × Post	-0.052***	-0.019
	(-6.28)	(-0.55)
Observations	17422	17686
Adjusted R^2	0.991	0.858
Bank Controls	Y	Y
Bank-Cohort FE	Y	Y
Year-Cohort FE	Y	Y
Year-County FE	Y	Y

Panel B: Competitive vs. concentrated	Ln(Local deposits)	
	Competitive	Concentrated
HighNPL × Post	-0.043***	-0.022
	(-4.56)	(-0.78)
Observations	17556	17552
Adjusted R^2	0.974	0.893
Bank Controls	Y	Y
Bank-Cohort FE	Y	Y
Year-Cohort FE	Y	Y
Year-County FE	Y	Y

Panel C: More vs. less banks	Ln(Local deposits)	
	Less banks	More banks
HighNPL × Post	-0.070***	-0.004
	(-5.37)	(-0.14)
Observations	17547	17547
Adjusted R^2	0.967	0.865
Bank Controls	Y	Y
Bank-Cohort FE	Y	Y
Year-Cohort FE	Y	Y
Year-County FE	Y	Y

Table 11: Bank loan quality and problem loan reporting (Sort samples by business environments)

This table examines the effect of banks' existing loan quality (NPL ratios) on subsequent reporting of their problem loans (nonperforming or non-accrual loans) given natural disasters in the counties where local banks are located after sorting samples to those in market stress and non-stress periods (Panel A), those in competitive and concentrated counties (Panel B), or those in counties with greater and smaller numbers of banks (Panel C). The sample consists of two-year event windows (one year for the pre-period and one year for the post-period) from 2001 to 2019 for each bank. A market stress is measured by an annual average of monthly spreads between 3-month Commercial Paper (CP) rate and 3-month T-bill rate. If the average spread is above the median, the period is defined as a market stress in Panel A. Market competitiveness is measured by the deposit market Herfindahl-Hirschman Index (HHI) in each county. If the HHI is below the median, the county is defined as a competitive market in Panel B. Finally, if the number of bank brands in a county, scaled by its population, is below the median, the county is defined as a market with less banks in Panel C. The regression also includes a set of control variables for bank characteristics listed in Table 2. The coefficients on these variables are not reported for compactness. All other regression specifications are the same as those in Table 2. Standard errors are clustered at the bank-level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. *t*-statistics are in parentheses. Variable definitions are provided in Appendix A.

Panel A: Stress vs. non-stress	Ln(NPL)		Ln(non-accrual)	
	Stress	Non-stress	Stress	Non-stress
	(1)	(2)	(3)	(4)
Treated × HighNPL × Post	-0.666***	-0.208*	-0.564***	-0.153
	(-3.46)	(-1.83)	(-2.80)	(-1.17)
Observations	17426	17774	17426	17774
Adjusted R^2	0.820	0.878	0.833	0.850
Bank Controls	Y	Y	Y	Y
Bank-Cohort FE	Y	Y	Y	Y
Year-Cohort-HighNPL FE	Y	Y	Y	Y
Year-County FE	Y	Y	Y	Y

Panel B: Competitive vs. concentrated	Ln(NPL)		Ln(non-accrual)	
	Competitive	Concentrated	Competitive	Concentrated
	(1)	(2)	(3)	(4)
Treated × HighNPL × Post	-0.496***	-0.184	-0.608***	0.010
	(-3.18)	(-1.33)	(-3.50)	(0.06)
Observations	17605	17593	17605	17593
Adjusted R^2	0.900	0.757	0.889	0.785
Bank Controls	Y	Y	Y	Y
Bank-Cohort FE	Y	Y	Y	Y
Year-Cohort-HighNPL FE	Y	Y	Y	Y
Year-County FE	Y	Y	Y	Y

Panel C: More vs. less banks	Ln(NPL)		Ln(non-accrual)	
	Less banks	More banks	Less banks	More banks
	(1)	(2)	(3)	(4)
Treated × HighNPL × Post	-0.344*	-0.213**	-0.442**	0.013
	(-1.95)	(-2.21)	(-2.42)	(0.10)
Observations	17595	17589	17595	17589
Adjusted R^2	0.902	0.814	0.899	0.800
Bank Controls	Y	Y	Y	Y
Bank-Cohort FE	Y	Y	Y	Y
Year-Cohort-HighNPL FE	Y	Y	Y	Y
Year-County FE	Y	Y	Y	Y

Appendix A: Variable Definitions

Variable	Definition	Level
<u>*Key dependent variable*</u>		
Ln(NPL)	Natural log of an annual average of a bank's quarter-end nonperforming loans (thousand $). Nonperforming loans are the sum of loans more than 90 days past due and still accruing and non-accrual loans	Year-Bank
Ln(non-accrual)	Natural log of an annual average of a bank's quarter-end non-accrual loans (thousand $)	Year-Bank
Ln(mortgage)	Natural log of a bank's total mortgage origination during a year (thousand $)	Year-Bank
Ln(refin mortgage)	Natural log of a bank's total mortgages originated to borrowers for refinancing during a year (thousand $)	Year-Bank
Ln(home mortgage)	Natural log of a bank's total mortgages originated to borrowers for new home purchases during a year (thousand $)	Year-Bank
Ln(high income mortgage)	Natural log of a bank's total loans originated to borrowers with annual gross income above $50,000 during a year (thousand $)	Year-Bank
Ln(low income mortgage)	Natural log of a bank's total loans originated to borrowers with annual gross income below $50,000 during a year (thousand $)	Year-Bank
Ln(SBL)	Natural log of a bank's total small business lending origination during a year (thousand $)	Year-Bank
Ln(large SBL)	Natural log of a bank's total small business lending origination with a loan size above $100,000 during a year (thousand $)	Year-Bank
Ln(small SBL)	Natural log of a bank's total small business lending origination with a loan size below $100,000 during a year (thousand $)	Year-Bank
Ln(high income SBL)	Natural log of a bank's total loans originated to small businesses with annual revenues above $1 million during a year (thousand $)	Year-Bank
Ln(low Income SBL)	Natural log of a bank's total loans originated to small businesses with annual revenues below $1 million during a year (thousand $)	Year-Bank
Ln(assets)	Natural log of an annual average of a bank's quarter-end total assets (thousand $)	Year-Bank
Ln(loans)	Natural log of an annual average of a bank's quarter-end total loans (thousand $)	Year-Bank
Ln(credits)	Natural log of an annual average of a bank's quarter-end total credit (thousand $). Total credit is defined as sum of total loans and unused loan commitments in the off-balance sheet	Year-Bank
Loans/assets	An annual average of quarter-end ratios of a bank's total loans over total assets (in percentage)	Year-Bank
Liquid/assets	An annual average of quarter-end ratios of a bank's liquid assets over total assets. Liquid assets are defined as the sum of cash and securities (in percentage)	Year-Bank
Credits/assets	An annual average of quarter-end ratios of a bank's total credits over total assets Total credit is defined as the sum of total loans and unused loan commitments in the off-balance sheet (in percentage)	Year-Bank
Estate/loans	An annual average of quarter-end ratios of a bank's real estate loans over total loans (in percentage)	Year-Bank
C&I/loans	An annual average of quarter-end ratios of a bank's commercial and industrial (C&I) loans over total loans (in percentage)	Year-Bank
LiquidityCreation	Berger and Bouwman's (2009) liquidity creation measure for each bank (total, asset-side, liability-side, or off-balance sheet side). Quarter-end values are collapsed into their annual averages for each bank.	Year-Bank

Variable	Definition	Level
Ln(Local deposits)	Natural log of a bank's county-aggregate deposits as of June 30 of each year in the county where at least 65 percent of the bank's total deposits are collected	Year-Bank
Key independent variable		
Treated	Dummy that takes a value of 1 for counties that experience at least one FEMA natural disaster in the post-period and no disaster in the pre-period. *Treated* takes a value of 0 for counties that experience no disaster in both pre- and post-periods and are adjacent to the counties with FEMA natural disasters	Cohort-County
HighNPL	Dummy that takes a value of 1 if an annual average of a bank's quarter-end NPL ratios is higher than the median as of the pre-period, 0 otherwise	Cohort-Bank
Post	Dummy that takes a value of 1 for the post-period, 0 for the pre-period	Cohort-Year
Control variable		
Ln(total assets)	Natural log of bank's total assets (thousand $) at year-end	Year-Bank
Ln(total deposits)	Natural log of bank's total deposits (thousand $) at year-end	Year-Bank
BHC	Dummy that takes a value of 1 for a bank that is affiliated in a bank holding company, 0 otherwise at year-end	Year-Bank
Capital	Ratio of the bank's tier 1 capital over total risk weighted assets at year-end (in percentage)	Year-Bank
Leverage	Ratio of the bank's tier 1 capital over total assets at year-end (in percentage)	Year-Bank
ROA	Ratio of the bank's net income over total assets during a year (in percentage)	Year-Bank

Appendix B: Additional Tables

Table B.1: Natural disasters and delinquency rate

This table examines the effect of natural disasters on delinquency rates of the local banks located in the affected counties. The sample coverage is the same as in Table 2 except that we use quarterly data for this test. *Delinquency* is the percentage of delinquent loans among total loans at quarter-end. A loan is classified as a delinquent loan if payments of interest and/or the principal of the loan are past due for 30-90 days (but still accruing). In this test, we employ three different dummy variables that identify the natural disaster events in the county. *ShockCurrentQ* is a dummy variable that takes a value of one if there is at least one natural disaster declaration in the county in the current quarter, zero otherwise. *ShockLaggedQ* is a dummy variable that takes a value of one if there is at least one natural disaster declaration in the county in the previous quarter, zero otherwise. *ShockCombinedQ* is a dummy variable that takes a value of one if there is at least one natural disaster declaration in the county in the previous or current quarters, zero otherwise. The regression also includes a set of control variables for bank characteristics listed in Table 2. Those control variables are as of the previous quarter-end. The coefficients on these variables are not reported for compactness. In Panel A, we use the full sample, and in Panel B, we limit samples to the observations in the periods under market stress. If an annual average of monthly spreads between 3-month Commercial Paper (CP) rate and 3-month T-bill rate is above the median, the period is defined as a market stress. All other regression specifications are the same as those in Table 2. Standard errors are clustered at the bank-level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. *t*-statistics are in parentheses.

Panel A: Full sample	Delinquency		
	(1)	(2)	(3)
ShockCurrentQ	0.034*		
	(1.75)		
ShockLaggedQ		0.035*	
		(1.71)	
ShockCombinedQ			0.046**
			(2.54)
Observations	134299	118877	134299
Adjusted R^2	0.524	0.533	0.524
Bank Controls	Y	Y	Y
Bank FE	Y	Y	Y
Quarter FE	Y	Y	Y

Panel B: With market stress	Delinquency		
	(1)	(2)	(3)
ShockCurrentQ	0.073**		
	(2.27)		
ShockLaggedQ		0.081**	
		(2.36)	
ShockCombinedQ			0.091***
			(2.81)
Observations	65779	56749	65779
Adjusted R^2	0.553	0.578	0.553
Bank Controls	Y	Y	Y
Bank FE	Y	Y	Y
Quarter FE	Y	Y	Y

Table B.2: Bank loan quality and quarterly problem loan reporting

This table examines the effect of banks' existing loan quality (NPL ratios) on subsequent reporting of their problem loans (nonperforming or non-accrual loans) given natural disasters in the counties where local banks are located. We convert the bank-year panel data used in Table 2 to bank-quarter panel. We limit sample to the observations in the treated counties and the year of the post-period in the original two-year event window. In this test, we employ four different dummy variables that identify the natural disaster events in the county in each quarter. *ShockCurrentQ* is a dummy variable that takes a value of one if there is at least one natural disaster declaration in the county in the current quarter, zero otherwise. *ShockLagged1Q* is a dummy variable that takes a value of one if there is at least one natural disaster declaration in the county in the previous quarter, zero otherwise. *ShockLagged2Q* is a dummy variable that takes a value of one if there is at least one natural disaster declaration in the county two quarters ago, zero otherwise. *ShockLagged3Q* is a dummy variable that takes a value of one if there is at least one natural disaster declaration in the county three quarters ago, zero otherwise. The regression also includes a set of control variables for bank characteristics listed in Table 2. Those control variables are as of the previous quarter-end. The coefficients on these variables are not reported for compactness. All other regression specifications are the same as those in Table 2. Standard errors are clustered at the bank-level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. *t*-statistics are in parentheses.

	Ln(NPL)				Ln(non-accrual)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HighNPL	1.266***	1.280***	1.290***	1.261***	1.426***	1.443***	1.447***	1.421***
	(19.87)	(20.09)	(20.19)	(19.84)	(19.28)	(19.47)	(19.52)	(19.26)
ShockCurrentQ	-0.043				-0.005			
	(-0.65)				(-0.08)			
ShockLagged1Q		0.087				0.138*		
		(1.16)				(1.85)		
ShockLagged2Q			0.310***				0.244***	
			(4.12)				(3.19)	
ShockLagged3Q				0.112				0.100
				(0.64)				(0.57)
HighNPL × ShockCurrentQ	0.054				0.026			
	(0.77)				(0.36)			
HighNPL × ShockLagged1Q		-0.103				-0.165**		
		(-1.33)				(-2.08)		
HighNPL × ShockLagged2Q			-0.273***				-0.257***	
			(-3.39)				(-2.95)	
HighNPL × ShockLagged3Q				-0.162				-0.180
				(-0.91)				(-0.97)
Observations	69638	69638	69383	68165	69638	69638	69383	68165
Adjusted R^2	0.758	0.758	0.759	0.760	0.769	0.769	0.770	0.770
Bank Controls	Y	Y	Y	Y	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y

Table B.3: Bank loan quality and problem loan reporting
(Limit samples to local banks in the treated counties)

This table examines the effect of banks' existing loan quality (NPL ratios) on subsequent reporting of their problem loans (nonperforming or non-accrual loans) given natural disasters in the counties where local banks are located. In this robustness test, we limit samples to local banks in the treated counties and compare local banks with high NPL ratios and those with low NPL ratios only in the treated counties. The sample consists of two-year event windows (one year for the pre-period and one year for the post-period) from 2001 to 2019 for each bank. The regression also includes a set of control variables for bank characteristics listed in Table 2. The coefficients on these variables are not reported for compactness. All other regression specifications are the same as those in Table 2. Standard errors are clustered at the bank-level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. *t*-statistics are in parentheses.

	Ln(NPL)	Ln(non-accrual)
	(1)	(2)
HighNPL × Post	-0.671***	-0.707***
	(-12.72)	(-11.61)
Observations	10136	10136
Adjusted R^2	0.852	0.858
Bank Controls	Y	Y
Bank-Cohort FE	Y	Y
Year-Cohort FE	Y	Y

Table B.4: Dynamics of problem loan reporting

This table examines the dynamic effects of banks' existing loan quality (NPL ratios) on subsequent reporting of their problem loans (nonperforming or non-accrual loans) given natural disasters in the counties where local banks are located. The original two-year event window is extended to five-year event window, which includes two years prior to natural disasters, the year with the disasters, and two years following the natural disasters. *Shock (k)*, where *k* ranges from -2 to +2, are a set of dummy variables that take a value of one if it is *k* years prior to (minus sign) or following (plus sign) the natural disasters, zero otherwise. The regression also includes a set of control variables for bank characteristics listed in Table 2. Those control variables are as of the previous year-end. The coefficients on these variables are not reported for compactness. All other regression specifications are the same as those in Table 2. Standard errors are clustered at the bank-level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. *t*-statistics are in parentheses. Variable definitions are provided in Appendix A.

	Ln(NPL)	Ln(non-accrual)
	(1)	(2)
Treated × HighNPL × Shock (-2)	-0.032	-0.008
	(-0.30)	(-0.07)
Treated × HighNPL × Shock (-1)	Reference	Reference
Treated × HighNPL × Shock (0)	-0.192*	-0.241**
	(-1.88)	(-2.15)
Treated × HighNPL × Shock (+1)	-0.058	-0.130
	(-0.46)	(-0.85)
Treated × HighNPL × Shock (+2)	-0.079	-0.105
	(-0.53)	(-0.59)
Observations	77267	77267
Adjusted R^2	0.831	0.822
Bank Controls	Y	Y
Bank-Cohort FE	Y	Y
Year-Cohort-HighNPL FE	Y	Y
Year-Cohort-County FE	Y	Y

Table B.5: Bank loan quality and problem loan reporting (Sort samples by their capital adequacy or profitability)

This table examines the effect of banks' existing loan quality (NPL ratios) on subsequent reporting of their problem loans (nonperforming or non-accrual loans) given natural disasters in the counties where local banks are located after sorting samples by their capital adequacy or profitability. The sample consists of two-year event windows (one year for the pre-period and one year for the post-period) from 2001 to 2019 for each bank. If a bank's capital ratio or ROA is above the median, the bank is assumed to be better capitalized or more profitable. The regression also includes a set of control variables for bank characteristics listed in Table 2. The coefficients on these variables are not reported for compactness. All other regression specifications are the same as those in Table 2. Standard errors are clustered at the bank-level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. *t*-statistics are in parentheses.

Panel A	Ln(NPL)		Ln(non-accrual)	
	Better capitalized	Worse capitalized	Better capitalized	Worse capitalized
	(1)	(2)	(3)	(4)
Treated × Post	0.248**	0.119	0.383***	0.081
	(2.34)	(1.06)	(3.19)	(0.68)
HighNPL × Post	-0.401***	-0.461***	-0.365***	-0.506***
	(-7.26)	(-6.54)	(-5.35)	(-6.25)
Treated × HighNPL × Post	-0.326***	-0.103	-0.395***	-0.075
	(-3.27)	(-0.92)	(-3.29)	(-0.61)
Observations	17058	18142	17058	18142
Adjusted R^2	0.876	0.869	0.873	0.870
Bank Controls	Y	Y	Y	Y
Bank-Cohort FE	Y	Y	Y	Y
Year-Cohort FE	Y	Y	Y	Y

Panel B	Ln(NPL)		Ln(non-accrual)	
	More profitable	Less profitable	More profitable	Less profitable
	(1)	(2)	(3)	(4)
Treated × Post	0.157	0.285**	0.241**	0.321**
	(1.60)	(2.14)	(2.23)	(2.17)
HighNPL × Post	-0.343***	-0.501***	-0.295***	-0.525***
	(-5.62)	(-7.36)	(-3.94)	(-6.46)
Treated × HighNPL × Post	-0.227**	-0.283**	-0.342***	-0.302**
	(-2.30)	(-2.22)	(-2.97)	(-2.04)
Observations	17510	17690	17510	17690
Adjusted R^2	0.888	0.859	0.880	0.868
Bank Controls	Y	Y	Y	Y
Bank-Cohort FE	Y	Y	Y	Y
Year-Cohort FE	Y	Y	Y	Y

Table B.6: Bank loan quality and problem loan reporting (Use quartile values for banks' NPL ratios)

This table examines the effect of banks' existing loan quality (NPL ratios) on the banks' subsequent reporting of their problem loans (nonperforming or non-accrual loans) given natural disasters in the counties where local banks are located. In this robustness test, we employ quartile variables instead of the dummy variables as the main independent variables. The sample consists of two-year event windows (one year for the pre-period and one year for the post-period) from 2001 to 2019 for each bank. *NPLQ* is a quartile value for banks' annual average NPL ratios as of the pre-period (1 is the value for the banks with lowest average NPL ratio and 4 is the value for the banks with highest average NPL ratio as of the pre-period). The regression also includes a set of control variables for bank characteristics listed in Table 2. The coefficients on these variables are not reported for compactness. All other regression specifications are the same as those in Table 2. Standard errors are clustered at the bank-level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. *t*-statistics are in parentheses.

Panel A	Ln(NPL)		
	(1)	(2)	(3)
Treated × Post	0.418***	0.396***	
	(2.95)	(2.61)	
NPLQ × Post	-0.458***		
	(-12.07)		
Treated × NPLQ × Post	-0.132***	-0.118**	-0.256***
	(-2.88)	(-2.39)	(-2.87)
Observations	35200	35200	35200
Adjusted R^2	0.884	0.901	0.892
Bank Controls	Y	Y	Y
Bank-Cohort FE	Y	Y	Y
Year-Cohort FE	Y	N	N
Year-Cohort-NPLQ FE	N	Y	Y
Year-County FE	N	N	Y

Panel B	Ln(non-accrual)		
	(1)	(2)	(3)
Treated × Post	0.429***	0.362**	
	(2.83)	(2.18)	
NPLQ × Post	-0.468***		
	(-11.66)		
Treated × NPLQ × Post	-0.126**	-0.102*	-0.275***
	(-2.55)	(-1.88)	(-2.85)
Observations	35200	35200	35200
Adjusted R^2	0.883	0.893	0.881
Bank Controls	Y	Y	Y
Bank-Cohort FE	Y	Y	Y
Year-Cohort FE	Y	N	N
Year-Cohort-NPLQ FE	N	Y	Y
Year-County FE	N	N	Y

Table B.7: Bank loan quality and problem loan reporting (Sort natural disasters by monetary damages)

This table examines the effect of banks' existing loan quality (NPL ratios) on the banks' subsequent reporting of their problem loans (nonperforming or non-accrual loans) given natural disasters in the counties where local banks are located. In this robustness test, we sort samples to those with severe natural disasters and those with non-severe disasters. The sample consists of two-year event windows (one year for the pre-period and one year for the post-period) from 2001 to 2015 for each bank. The severity of a disaster is measured by the disaster's monetary damages to properties in the county. If the aggregate monetary damages in a county during the year scaled by the county's population are above the median, the treated county is assumed to experience severe disasters. Otherwise, the treated county is assumed to face non-severe disasters. The regression also includes a set of control variables for bank characteristics listed in Table 2. The coefficients on these variables are not reported for compactness. All other regression specifications are the same as those in Table 2. Standard errors are clustered at the bank-level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. *t*-statistics are in parentheses.

	Ln(NPL)		Ln(non-accrual)	
	Severe	Non-severe	Severe	Non-severe
	(1)	(2)	(3)	(4)
Treated × HighNPL × Post	-0.278**	-0.206	-0.326**	-0.131
	(-2.16)	(-1.53)	(-2.07)	(-0.86)
Observations	6476	6476	6476	6476
Adjusted R^2	0.878	0.901	0.870	0.899
Bank Controls	Y	Y	Y	Y
Bank-Cohort FE	Y	Y	Y	Y
Year-Cohort-HighNPL FE	Y	Y	Y	Y
Year-County FE	Y	Y	Y	Y

Table B.8: Bank loan quality and problem loan reporting (Control for bank holding company level governance structures)

This table examines the effect of banks' existing loan quality (NPL ratios) on subsequent reporting of their problem loans (nonperforming or non-accrual loans) given natural disasters in the counties where local banks are located. In this robustness test, we control for a bank holding company (BHC) level governance structures by limiting samples to local banks affiliated with a BHC, which has at least three subsidiary local banks in the year, and adding year-BHC fixed effect in the regressions. BHC is the identifier of a bank holding company. The sample consists of two-year event windows (one year for the pre-period and one year for the post-period) from 2001 to 2019 for each bank. The regression also includes a set of control variables for bank characteristics listed in Table 2. The coefficients on these variables are not reported for compactness. All other regression specifications are the same as those in Table 2. Standard errors are clustered at the bank-level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. *t*-statistics are in parentheses.

	Ln(NPL)	Ln(non-accrual)
	(1)	(2)
Treated × HighNPL × Post	-7.076**	-14.770***
	(-2.23)	(-3.68)
Observations	1598	1598
R^2	0.997	0.996
Bank Controls	Y	Y
Bank-Cohort FE	Y	Y
Year-Cohort-HighNPL FE	Y	Y
Year-County FE	Y	Y
Year-BHC FE	Y	Y

Table B.9: Bank loan quality and problem loan reporting
(Use NPL ratios as outcome variables)

This table examines the effect of banks' existing loan quality (NPL ratios) on subsequent reporting of their problem loans given natural disasters in the counties where local banks are located. In this robustness test, we employ banks' NPL ratios as the outcome variables. The sample consists of two-year event windows (one year for the pre-period and one year for the post-period) from 2001 to 2019 for each bank. In Column (1), we use banks' year-end NPL ratio (in percentage) as the outcome variable. In Column (2), we use annual average values for banks' quarter-end NPL ratios as the outcome variable. The regression also includes a set of control variables for bank characteristics listed in Table 2 except *BHC* dummy and its interaction with *Post* dummy. The coefficients on these variables are not reported for compactness. All other regression specifications are the same as those in Table 2. Standard errors are clustered at the bank-level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. *t*-statistics are in parentheses.

	NPL ratio (year-end)	NPL ratio (average)
	(1)	(2)
Treated × HighNPL × Post	-0.273**	-0.138*
	(-2.31)	(-1.82)
Observations	35076	35093
Adjusted R^2	0.755	0.840
Bank Controls	Y	Y
Bank-Cohort FE	Y	Y
Year-Cohort-HighNPL FE	Y	Y
Year-County FE	Y	Y

Table B.10: Bank loan quality and problem loan reporting (Sort samples to federally and state-chartered banks)

This table examines the effect of banks' existing loan quality (NPL ratios) on the banks' subsequent reporting of their problem loans (nonperforming or non-accrual loans) given natural disasters in the counties where local banks are located. In this robustness test, we sort samples to federally chartered and state chartered banks. The sample consists of two-year event windows (one year for the pre-period and one year for the post-period) from 2001 to 2019 for each bank. The regression also includes a set of control variables for bank characteristics listed in Table 2. The coefficients on these variables are not reported for compactness. All other regression specifications are the same as those in Table 2. Standard errors are clustered at the bank-level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. *t*-statistics are in parentheses.

	Ln(NPL)		Ln(non-accrual)	
	Federally chartered	State chartered	Federally chartered	State chartered
	(1)	(2)	(3)	(4)
Treated × Post	0.360*	0.172**	0.521**	0.197**
	(1.77)	(2.11)	(2.51)	(2.19)
HighNPL × Post	-0.436***	-0.464***	-0.477***	-0.461***
	(-4.35)	(-9.52)	(-4.35)	(-8.04)
Treated × HighNPL × Post	-0.463**	-0.159**	-0.569***	-0.189**
	(-2.38)	(-2.00)	(-2.68)	(-2.06)
Observations	7202	27998	7202	27998
Adjusted R^2	0.883	0.873	0.883	0.876
Bank Controls	Y	Y	Y	Y
Bank-Cohort FE	Y	Y	Y	Y
Year-Cohort FE	Y	Y	Y	Y

Table B.11: Charge-off and financial ratios

This table examines the effect of banks' loan charge-off on their financial ratios. The sample coverage is the same as in Table 2 except that we use quarterly data for this test. *Ln(Charge-off)_Q* is a natural log of total amount of loan charge-off during a quarter. *Ln(Provision)_Q* is a natural log of the total amount of loan loss provision during a quarter. *ROA_Q* is the ratio of the bank's net income over total assets during a quarter (in percentage). *Leverage_Q* is the amount of the bank's tier 1 capital scaled by its total assets as of the quarter-end (percentage). The regression also includes a set of control variables for bank characteristics listed in Table 2. Those control variables are as of the previous quarter-end. The coefficients on these variables are not reported for compactness. All other regression specifications are the same as those in Table 2. Standard errors are clustered at the bank-level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. *t*-statistics are in parentheses.

	Ln(Provision)_Q	ROA_Q	Leverage_Q
	(1)	(2)	(3)
Ln(Chargeoff)_Q	0.233***	-0.134***	-0.016***
	(33.61)	(-11.29)	(-3.10)
Observations	137046	137576	137576
Adjusted R^2	0.711	0.393	0.961
Bank Controls	Y	Y	Y
Bank FE	Y	Y	Y
Quarter FE	Y	Y	Y