Natural Disasters, Loan Loss Accounting and Subsequent Lending*

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Abstract

This paper examines the impact of disasters on banks' loan loss accounting, and the impact of loan loss accounting on banks' ability to respond to disaster-related increases in demand for loans. We map the locale of natural disasters to banks, thereby identifying banks treated by natural disasters, and matching banks that are enjoying relatively calm lending environments. We implement a difference–in–difference research strategy for our analysis. We first show loan loss provisions reflect an increasing weight on current and lagged loan loss indicators during the four quarters that encompass the disaster. Importantly, for large banks, the loan loss provisions reflects a higher weighting on forward looking estimates of non–performing loans post the disaster. This finding for large banks raises a concern that disasters impact loan loss provisions in such a way that they confound the interpretation of provisioning-timeliness measures which have been used in prior research. Our second research question identifies banks that use either more conservative, or more timely provisioning practices, in periods preceding disasters, and examines whether these banks are able to respond more quickly to new loan demands that are created by disasters. Our results suggest that smaller banks, which have conservative provisions (i.e., they over-reserve) during non-disaster periods, demonstrate greater loan growth following a disaster. However, if our model incorporates an increased role for Tier 1 capital in the post-disaster period, the correlation between provisioning-conservatism and lending is subsumed. Finally, we fail to find evidence that provisioning–timeliness plays any role in stimulating lending in post-disaster periods. This indicates that prior research that has suggested the existence of a positive feedback between "timeliness" and lending during economic downturns, does not generalize to banks' response to localized increases in demand for loans as identified by disasters.

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1 Introduction

Regulators and economists have questioned the advisability of loan loss procedures under Generally Accepted Accounting Practices (GAAP) known as the "incurred loss model," because of its supposed adverse consequences for lending. Under the incurred loss model, banks typically wait until a so-called "triggering event" occurs (e.g., non-payment of interest on a loan) before recording a loan loss provision. This practice is likely to cause loan loss reserves to lag managerial expectations of losses. Regulators argue that this accounting practice contributed to restrained lending during economic downturns, aka "capital crunches". The story goes that pro-cyclicality in loan loss accounting (smaller reserves during the end of booms and at the beginning of busts, and larger provisions at the bottom of cycles and into the next boom period) can manifest, adversely, as a reduced willingness or flexibility by bankers to extend loans at the bottom of cycles, when liquidity is in high demand.

In fact US and international standard setters have promulgated changes to loan loss provisioning methods, partly as a response to this presumed linkage between loss accounting and lending. By 2020 under ASC 326–20, US banks will begin to recognize loan loss provisions at the date a loan is booked, rather than waiting for triggering events. While the new standards will bring management expectations regarding future losses to balance sheets before triggering events, they are also likely to increase noise in loan loss provisions and could even reduce financial statement comparability.[1] The CECL standard will not eliminate management discretion over the magnitude of loan loss reserves and the timing of loan loss provisions because the original estimate of the loan loss reserves, and subsequent revisions in bad debt estimates will still be subject to judgement. In July 2019, the FASB issued a proposal to delay the implementation of this new standard for non-SEC public banks among others (see Maurer, 2019).

We seek additional evidence in support of the debate around accounting for credit risks. We use an innovative identification strategy–we trace natural disasters to the banks affected by them–to

[1] Chae et al. (2018) point out that small variations in assumptions that go in the provisioing model, can create big differences in estimated reserves. Covas and Nelson (2018) apply the CECL model retroactively and suggest that the CECL standard would not have smoothed out pro-cyclical lending.

understand loan loss provisioning behavior and its relation to lending. Typically prior research focusing on the determinants of capital crunches links loan loss accounting to lending, using a few, or singular, general economic downturns (e.g., Beatty and Liao (2011) or Jayaraman et al. (2018)).[2] Similar to what occurs during an economic downturn, banks subject to disasters can expect an increase in credit losses on some current loans, but also encounter profitable opportunities to lend to local businesses, e.g., to re–build in the aftermath of the disaster. However, in our case, we can identify such events at different points in time (i.e., using disasters that occur in different quarters and years), and which affect only subsets of banks at these different time points.

We match disaster–treated banks in a particular quarter to contemporaneous unaffected control banks that are not subject to disasters. By comparing treated banks to control banks, before and after disaster shocks, we implement a difference in difference identification strategy. Because disaster-events do not cluster on all banks at one point in time, our ability to draw valid inferences should improve (relative to studies that focus on a single or few events). We use this matched–paired sample, aligned in event time, to investigate two questions: first, how do banks choose loan loss estimates when borrowers have been subject to a disaster, and second, do banks with more conservative and or timely loan loss provisioning tactics before disasters demonstrate an increased ability to lend, as conjectured by some advocates of the ASC 326–20 standard?

With regard to our first research question on how bankers choose to record loan losses following disasters, note that disasters are a form of "triggering event" that ought to stimulate bank-managers to forecast future non-performing loans and to incorporate these estimates into loan loss accruals. Whereas banks are often viewed (by accounting researchers) as waiting for a cash flow indication, such as a missed loan payment, that a loan's default risk has increased, disasters allow banks to record losses on loans when they are still performing.[3] Note that academic researchers cannot

[2] Beatty and Liao (2011) use samples before and after general downturns in the early 2000's and in 2008–2009. Jayaraman et al. (2018) use the emerging debt crisis in the late 1990's.

[3] By the word "performing" we refer to a loan where the borrower has paid according to the debt contract, principal and interest on time.

observe all the triggering events that will cause revisions to credit loss estimates.[4]

Some research (e.g., Beatty and Liao (2011)) has assumed that contemporaneous and lagged changes in non-performing loans are good proxies for triggering events, and these studies classify the provisions relation to *future* non-performing loan changes to indicate that management has exercised some discretion to make loan loss provisions more timely. Yet, a disaster is an event that we, as researchers, can observe and, which is likely to make bankers update their loan loss provisions, based on their expectation of future non-performing loans, before any cash flow indicators have been triggered. We conjecture that in the quarters just after disasters, loan loss provisions will display a greater weight on management's expectations of future non-performing loans (relative to during calmer lending environments). But, in the case of disaster-impacts on loan loss provisions, one would be hard-pressed to say that this is an indication of high accrual quality.

As such, our analysis contributes to the collective understanding of the factors that lead bankers to incorporate forward information in their loan loss provisions.[5] Bhat et al. (2016) and Bhat et al. (2018) provide evidence that banks differ in systematic ways in their incorporation of future information in their loan loss provisions e.g., based on how concentrated the loan portfolio is in commercial loans, and based on the sophistication of management information systems. We suggest that the incorporation of future information also depends on the type of triggering events a bank is exposed to, with disasters being an example.

To examine the effect of disasters on loan loss provisioning policies, we regress loan loss provisions on changes in non-performing loans, measured for $t+1$, t, $t-1$, and $t-2$, along with other control variables that have been identified in prior research. At the time a bank sets its loan loss provision, it has access to information about non-performing assets at time t and earlier. By including the time $t+1$ non-performing loan information, we are assuming the bank managers forecast this data, even though triggering events may not yet have occurred.

[4]For instance a banker could observe a Chapter 11 filing by a borrower who has not defaulted in any way on loans. This filing would cause the banker to update loan loss estimates in advance of a cash flow indicator.

[5]This literature is reviewed in Beatty and Liao (2014).

When a bank's operations are hit by a natural disaster, our tests of the disaster-impact on the loan loss provision is measured both by a shift in the intercept for disaster impacted banks (the difference-in-difference average impact) and by allowing the regression coefficients for the treated banks to change (using a dummy interactive variable) for the four quarters encompassing the disaster event and the three subsequent quarters. The shift in intercept allows for affected banks to "top–up" their loan loss provisions following a disaster, and we make no prediction regarding the sign and significance of this intercept. A positive shift would be consistent with a "general provisioning" increase that is not supported by current model variables. However, our expectation is that the coefficient weight on the change in non-performing loans for period $t+1$ (again, measured ex post as a proxy for expectations) will be systematically higher for banks treated by disasters.

Our results are as follows. On average the response of loan loss provisions to period t+1 changes in non-performing loans is about twice the size of the response to period t+1 changes in non-performing loans during non-disaster periods. The relative growth in the size of this coefficient is much larger for banks with assets greater than $500 million, and, in fact for these larger banks the base weight on forward measures of non-performing loans (i.e., in non-disaster periods) is statistically insignificant. In contrast, for smaller banks, the reaction to disasters in this weighting is reserved for the fourth quarter, suggesting that management incorporates forward looking information into the disaster related losses only in the fourth quarter.

We also investigate earnings smoothing via loan loss provisions following disasters. We find, for all banks in non-disaster periods, that loan loss provisions are higher (lower) when earnings before provisions are higher (lower), suggesting that provisions are used to smooth income. At big banks, during disaster periods, this evidence of earnings smoothing strengthens, suggesting that disasters allow larger banks room to exercise discretion for this purpose.

Under our second research question, we examine how bank provisioning policies that were in place before disasters, subsequently correlate to banks' response to the increase in the demand for loans which have been triggered by disasters. We examine whether banks with more generous, and or more forward-looking, pre-disaster loan loss policies respond more flexibly to an increase in demand for loans. This inquiry is similar to the research questions addressed in Beatty and Liao (2011) and Jayaraman et al. (2018). These two papers respectively find that more timely (more smoothed) provisions allow banks more loan growth during recessions (during the emerging market crisis). Our use of demand shocks as measured by natural disasters and our more extensive sample of banks will speak to the generality of these findings.[6]

Again, we use disasters to identify economic conditions that cause banks to become more credit constrained, similar to the more general economic downturns that are the focus of these prior studies. We categorize banks based on two provisioning policies–provisioning conservationism and provisioning timeliness. Our measure of conservatism is captured by the signed residual from a regression of loan loss provisions on fundamental determinants, in non-disaster periods.[7] The construct, timeliness of loan loss provisions, follows from Beatty and Liao (2011); it captures the degree to which a bank relies on current and next period changes in non-performing loans in setting provisions. Using a regression framework, we test whether provision-conservatism and -timeliness are positive predictors of loan growth in the period following a disaster.

Our base results suggests bank profits and capital strength support growth in lending during normal times. In post-disaster periods, disaster-impacted banks increase their lending on average. For small banks we find that the reliance on Tier 1 capital intensifies in the post disaster quarters, suggesting that some of these banks become capital constrained when demand for loans increases. This suggests that natural disasters result in localized credit crunch conditions for smaller banks.

In addition, we find that conservatism in loan loss accounting associates to greater lending for small banks after a disaster period, but the precise reason for this relation is unclear. Specifically, small banks appear to be better able to respond to the shock to demand for loans if they have both a higher tier 1 capital ratio and if loss provisioning policies were more conservative. This finding

[6] Cortés and Strahan (2017) also use natural disasters to identify shocks to demands for loans.

[7] A positive residual is a larger income statement expense, and therefore this measures a conservative earnings number.

could indicate that bank managers who are more conservative in general, run banks that are better able to respond to loan growth. We find no evidence that, small banks, with more forward looking, timely, loan loss policies exhibit greater growth in loans in post disaster periods. Meanwhile, big banks (with assets greater than $500 million) show loan growth following disasters, but these banks show no evidence of being capital constrained in post-disaster periods and there is no evidence that loan loss provisioning policies impact this growth.

In prior research examining the links between provisioning and lending, Beatty and Liao (2011) suggest that during the recent downturns, the constraints on lending appear to tighten for larger banks (whereas in our case, following natural disasters, it is smaller banks that appear to face these constraints). According to this prior research, large banks exhibit higher growth in loans during two major economic downturns, if their loan loss provisions are more forward-looking. In contrast, we find some evidence that for small banks, more conservative loan loss provisioning policies appear to interact to loosen capital constraints in disaster periods. And, we find *no* evidence that more forward-looking provisioning policies serves to alleviate capital capital constraints for either big or small banks.[8]

Section 2 describes the motivation for our paper. Section 3 discusses our empirical strategy for our analysis. Section 4 provides discussion of the key variables used in our empirical analysis, along with the descriptive statistics of the main bank and disaster sample. Section 5 discusses the empirical results, and finally Section 6 offers the conclusion.

[8] Since our research suggests that capital crunches related to disasters apply to small banks, but not large banks–and since Beatty and Liao (2011) finds that it is big banks that are constrained during economic crises–it is probably not possible to reconcile the results from our matched–paired design using natural disasters to mimic crisis periods, with this prior important study.

2 Motivation

2.1 How do Natural Disasters Impact Loan Loss Provisions?

An extensive prior literature attempts to infer how banks estimate loan loss provisions and the degree to which these estimates are used to manage balance sheets and income statements. These studies usually regress a loan loss accrual variable, such as the loan loss provision, on fundamental indicators of loan losses, such as non-performing loans, changes in non-performing loans, loan charge–offs, and loan loss reserves. In addition, the models usually include variables to capture financial reporting objectives such as earnings smoothing and regulatory capital management variables. Moyer (1990) and Wahlen (1994) provide an excellent discussion to what researchers identify fundamental indicators of normal loan losses and loan charge-offs, and Beatty and Liao (2014) review of accounting-based banking research provides a helpful summary of the various approaches that researchers have taken to capture expected loan loss provisions in the absence of earnings or balance sheet management.

Over time, and especially following the recent financial crisis, research-attention has shifted from how banks managers use loan loss provisions to *manage* their financial reports, to constructing measures of the quality of reporting. For example, the degree to which "forward-looking" fundamentals predict loan loss provisions, sometimes assumed to indicate high quality of loan loss provisions. This view is apparent in research such as Beatty and Liao (2011), Bushman and Williams (2012), Bushman and Williams (2015), and Akins et al. (2017). The error term from a loan loss accrual model has also been viewed as a measure of accounting quality, e.g., Jiang et al. (2016) interpret the magnitude of the absolute value of the residual from a "normal" loan loss provisioning model as a measure of bank opacity. Also, earnings smoothing, typically captured as the positive correlation between the loan loss provision and earnings before provisions, is viewed by some economists in a favorable light because it indicates countercyclical provisioning; in comparison, accounting researchers have typically viewed this correlation in a negative light as indicating some abuse of management discretion.

In this paper, we examine whether loan loss provisions are impacted by disasters. We contribute to the prior literature on loan loss provisioning models through our insight that the provisioning model might change when a bank is exposed to a special kind of triggering event, namely a disaster. This portion of our paper is in the spirit of research such as Bhat et al. (2016) and Bhat et al. (2018). These two prior studies propose that the appropriate model of loan loss provisions is highly contextual. Bhat et al. (2018) for example, suggest that the quality of loan loss provisions are likely to be influenced by the sophistication of analytical models that a bank uses to understand and report on loans. Accordingly, Bhat et al. (2018) code the disclosures made by banks regarding their use of sophisticated modelling. They find that the information contained in these disclosures is predictive of the degree to which loan loss provisions are forward looking. Similarly Acharya and Ryan (2016) and Bhat et al. (2016) emphasize the need to control for loan concentrations in homogeneous (i.e., consumer loans) versus heterogenous loans (i.e.,commercial loans) as important context in judging the quality of bank's loan loss provisions. For example commercial loans are inherently more difficult to audit, and have more uncertainty in their credit-worthiness; hence banks that have large concentrations of these loans can more easily exert discretion over loan loss provisions without fear of detection.

We contribute to this stream of literature by examining the role of disasters on loan loss accounting models. We believe that disasters are a form of triggering event that can allow banks more latitude to smooth earnings or capital. We imagine that these events alert managers to future changes in non-performing loans, even though standard triggering cash flow events might not have occurred. To the extent that the impact of disasters on forward looking non-performing loans is non-trivial, they provide another context in which loan loss provisions will contain forward looking information.

Our research design, more fully described in a subsequent section, allows us to test for four possible accounting responses to disasters. We posit that the four accounting responses are not mutually exclusive. First, banks in a disaster-area could choose to "top-up" the loan loss reserves, in a general manner that is not directly tied to expectations of future changes in incurred losses. Usually under the incurred loss model for loan losses, banks are purportedly not to engage in general-reserving, but since the future effects of natural disasters may be difficult to forecast, and to audit, our regression could detect any, undisciplined general-reserving as an increase in the model intercept in the post disaster quarters.

Secondly, banks could re–assess, and increase, the default probabilities attached to past indicators of credit risk, which, in our model, are measured by lagged changes in non-performing loans. We could detect this action by an increase in the slope coefficient on lagged indicators of credit risk in the post disaster period. For example, non–payment of interest in a prior quarter might be assessed as even more likely to indicate future default shortly after a disaster.[9]

Thirdly, the banks could re–assess and increase estimated default risk attached to current, and to future, credit risk indicators. We are especially interested in whether disasters cause banks to weight *future* changes in non-performing loans more heavily in setting loan loss provisions. Under normal circumstances, researchers have interpreted the weight on future changes in non-performing loans as an indicator that a bank is more willing to reflect future losses, in a more *timely* manner. We expect that banks' loan loss provisions *will* be more forward-looking in the post-disaster period because the triggering event (a disaster) naturally leads to forecasting of future credit risks, before the usual triggering events occur (e.g., a missed loan payment). Hence disasters might associate with more forward-looking loan loss provisions, but we don't think this means that managers have become more willing in general to recognize future losses at time t, which is the general thought behind the use of the word *timeliness*.

Finally, related to the first possibility, banks could exploit the uncertainty following disasters to increase the use of the provision for smoothing income or for managing regulatory capital. We can detect this through a post–disaster change in the regression weight on earnings, or on regulatory

[9] Disruption of businesses following the disaster would further constrain cash flows available to pay off loans.

capital.

2.2 Do Banks with more-timely Loan Loss Provisions Respond more Flexibly to an Increase in Loan Demand?

Our second research emphasis uses the natural disaster setting to re-examine the link between loan loss provisioning–quality, and lending, when bank is capital constrained. Some research such as Beatty and Liao (2011) and Jayaraman et al. (2018) has provided evidence that bank-specific application of standards that guide loan loss provisioning is associated with eased lending when the firm faces capital constraints. This research provides support for the position held by policy makers that banks delays' of provisioning or lack of provisioning smoothing, can exacerbate downturns.[10]

We believe this research avenue should be further explored for two reasons. First, we think that the hypothesis that loan loss accounting practices caused a deepening of the last financial crisis, is a hypothesis that should be subject to considerable tension. Implicitly, regulatory criticisms that link provision policies to lending presume that absent forward-looking loan loss provisioning or smoothing, bank managers, bank regulators, and (or) market intermediaries (who would pressure bank managers) fail to recognize the need to raise capital until the cost of raising capital has increased and banks face binding liquidity and capital constraints.[11] In other words, the logic that leads to the suggestion that the application of loan loss accounting model will exacerbate downturns, seems to give a fair degree of power to accounting numbers. It seems to rely on managers' willfully ignoring the underlying reality of their businesses and placing too much emphasis on accounting translations of that reality.[12]

[10] Beatty and Liao (2011) mention the Financial Stability Form Report (2009) as well as comments made by John C. Dugan in March of 2009. These are two examples of regulators suggesting that accounting for loan losses contributed to restrained lending.

[11] The existence of deposit insurance creates an incentive for bank shareholders to hold excess leverage. Regulatory monitoring and capital requirements help to insure that banks raise capital if leverage becomes too high.

[12] If banks face binding contracting terms that are denominated in accounting numbers, say through Tier 1 capital constraints, and if there is sufficient information asymmetry between bank managers and bank regulators, this could explain how pure application of accounting numbers could lead to an exacerbation of credit crunches. One reason to question this is that nearly all banks hold capital well in excess of regulatory minimums, suggesting that these

Secondly, while the prior research is very well-executed, the research has encountered difficult obstacles to valid inferences. For example, Acharya and Ryan (2016) review of these studies points out that loan loss provisioning is contextual and should be influenced by a host of variables that are not necessarily easy to capture in a linear regression framework.. Such factors include such banks' loan composition, local lending shocks, and even managerial attitudes towards risk. It is not difficult to imagine there are omitted contextual variables that could alter interpretations of the results that rely on major economic downturns for the research setting.[13] In addition, valid identification strategies are difficult to come by. The prior studies focus on a few crisis periods, and this almost certainly limits the generality of conclusions that can be drawn. Relatedly, this literature relies on the researcher being able to convincingly separate loan demand shifts from loan supply shifts. We believe that the use of natural disasters to identify demand shifts creates numerous crisis periods that affect subsets of banks at different points in time, assisting us in providing generalizable inferences. Also, the use of the matched pair design assists in controlling for omitted variables.

3 Empirical Strategy

The first step in our research design is to tie the effects of natural disasters to the location and quarter of banks by U.S. counties. By doing this we tag banks that are simultaneously subject to a increase in the demand for loans, as well as, subject to deterioration of the loans on the books. Section 4 describes our sample construction process where we match the affected banks (Shocked) to unaffected control banks.

If disaster-impacted banks have more forward-looking (or more conservative) loss provisions before the disaster occurs, and, if these provisioning attitudes drive banks to hold more real equity,

constraints are not binding.

[13] Acharya and Ryan (2016), comment that the omitted variables can lead some readers to suspect an alternative explanation that "stronger banks make both better financial reporting choices and less cyclical decisions."(see p. 283 Acharya and Ryan, 2016).

then we expect that the differences between the treatment and control groups can be explained by variation in loan loss provisioning policies. (This idea is illustrated in Figure 1 and Figure 2, discussed below). Hence, in order to test hypotheses regarding the relation between loss policies and bank flexibility to lend, we must first separate banks by their loan loss policies. This will be our first set of regressions. In addition, by allowing the loan loss policy regressions to adapt in the period following a disaster, the first set of regressions are also used to address our first research question, how loan loss provisioning is altered by disasters. Our second set of regressions will explore the relation between provisioning attitudes and lending, following demand shocks, as captured by disasters, again, employing a control sample of unaffected banks to help identify the impact of provisioning policies on lending growth.

3.1 Identifying Loan Loss Reactions to Disasters

We define dummy variables $Shock_{ct}$ that identify a county c and the quarter t, where banks are located and have been hit by a disaster.[14] We define a second dummy variable $Post_{dt}$ that identifies a particular disaster in quarter d and subsequent three quarters, d, (e.g., Hurricane Katrina). If a bank is in a county affected by a disaster, the multiplication of $Shock_b$ and $Post_t$ is a dummy variable for a bank that is 1 in the quarter of and the three quarters following a disaster. Suppose that the only impact of a disaster is to possibly increase the average loan loss provision for an affected bank, we measure this average increase this using β_1 in the following regression model:

$$
\begin{aligned}
LLP_{bt} = {} & \beta_1 Shock_b \times Post_t + \beta_1 \Delta Non-Perf.Assets_{b,t+1} + \beta_2 \Delta Non-Perf.Assets_{b,t} \\
& + \beta_3 \Delta Non-Perf.Assets_{b,t-1} + \beta_4 \Delta Non-Perf.Assets_{b,t-2} \\
& + Controls + \text{Bank FE} + \text{State} \times \text{Time FE} \qquad (3.1)
\end{aligned}
$$

In this regression, Δ refers to a difference in a variable in two adjacent quarters, while *Non-Perf.*

[14] We identify banks impacted by a disaster based on the county of the disaster in a particular quarter, and whether the bank operates in the county.

Assets refers to "non-performing assets," e.g., loans and assets that are ninety days past due and in non–accruals. We scale both the dependent and the independent variables are one-period lagged, gross loans. Changes in non-performing loans are likely to indicate that the risk of default has changed, and this is the reason that these variables are often used in models of loan loss provisions. The control variables in this equation are similar to that discussed in Beatty and Liao (2014). Given this regression, the coefficient β_1 on the $Shock_b \times Post_t$ dummy variable measures the average increase of loan loss provisions in for the four quarters encompassing all disasters in our sample.

In the prior section, we emphasize that the impact of a disaster on loan loss accounting could manifest as an increased incorporation of future expectations on loan loss provisions. This possibility is captured in the following regression which allows for a shift in the weight placed on the non-performing loan changes by interacting $Shock_b \times Post_t$ with the non-performing loan measures. In addition, in Equation (3.2) we add Tier 1 capital (Tier1 Ratio), measured at time *t-1* and earnings before the loan loss provisions (EBP) to see if loan loss provision behavior is consistent with capital management or earnings smoothing.

$$\begin{aligned}
LLP_{bt} = {} & \beta_1 Shock_b \times Post_t + \beta_2 Shock_b \times Post_t \times \Delta Non-Perf.Assets_{b,t+1} \\
& + \beta_3 Shock_b \times Post_t \times EBP_{b,t} \\
& + \beta_4 Shock_b \times Post_t \times Tier1Ratio_{b,t-1} + \alpha_1 \Delta Non-Perf.Assets_{b,t+1} \\
& + \alpha_2 \Delta Non-Perf.Assets_{b,t} + \alpha_3 \Delta Non-Perf.Assets_{b,t-1} \\
& + \alpha_4 \Delta Non-Perf.Assets_{b,t-2} \\
& + Controls + \text{Bank FE} + \text{State} \times \text{Time FE}
\end{aligned} \tag{3.2}$$

A positive and statistically significant β_2 indicates that in the four quarter following and including a disaster, affected banks let their expectations of future non-performing loans to influence the level of the loan loss provision to a greater extent, in comparison to non-disaster periods (α_1). Similarly, a positive coefficient β_3 (β_4) can be interpreted as an increased use of the loan loss allowance to smooth earnings (Tier 1 capital). We estimate this regression for small banks (with $<$ 500 million assets) as well as for large banks. Our intuituion is that the weighting on future changes in non–performing loans will be sensitive to the sophistication of bank managers, and that large banks are likely to have more sophisticated loan loss modelling abilities. We also are aware that the relation between loan loss indicators and the provision for loan losses may change in the fourth quarter.

3.2 Linking Loan Loss Provisioning Policies to Growth in Lending

Next we examine whether loan loss provisioning habits impact banks' ability to lend following a crisis period. The dependent variable in our regression is loan growth, Y_{bt} measured as the change in loans divided by beginning period loans. Following a disaster, we expect demand for loans to shift out, relative to the matched pairs that should face the same demand curve. It is also possible that the supply curve for our banks shifts in because the expectation of worsening loan defaults for the most adversely affected borrowers, should lead to additional loan loss provisioning for our treated banks, relative to our control banks. We specifically estimate the following model:

$$\begin{aligned}
Y_{bt} = {} & \beta_1 Shock_b \times Post_t + \beta_2 Shock_b \times Post_t \times LLPPolicy_{b,t-1} \\
& + \beta_3 Shock_b \times Post_t \times EBP_{b,t} \\
& + \beta_4 Shock_b \times Post_t \times Tier1Ratio_{b,t-1} + \beta_5 LLPPolicy_{b,t-1} \\
& + \beta_6 EBP_{b,t} + \beta_7 Tier1Ratio_{b,t-1} \\
& + \beta_8 LLPPolicy_{b,t-1} \times Tier1Ratio_{b,t-1} \\
& + \beta_9 Shock_b \times Post_t \times LLPPolicy_{b,t-1} \times Tier1Ratio_{b,t-1} \\
& + Controls + \text{Bank FE} + \text{State} \times \text{Time FE}
\end{aligned} \tag{3.3}$$

where, *LLPpolicy*$_{bt-1}$ indicates the "loan loss policy" we have assigned to the bank. We use two measures for this variable. The first measure is conservatism and this is based on a moving average of the residual from Equation (3.1), over the prior 12 quarters, excluding any disaster quarters, and provided we have least 8 quarters in the moving average. Each quarter t each bank is assigned to either the high provisioning banks which are above the median for that quarter (*HighRES12* in our tables). This variable captures conservatism because it shows which banks set aside more than is predicted from the normal expected loan loss provision from Equation (3.1). *Tier1Ratio* refers to banks' actual Tier 1 Capital ratio at the beginning of the quarter t.

Our second measure is captured based on the increase in r-squared which occurs when Equation (3.1) is estimated without current and future changes in *NPL* versus when these two terms are included. Hence this measure shows the extent to which a banks loan loss provision is forward looking. This is estimated using a time series of 12 quarters for each bank in non-disaster periods. This is the identical construct used in Beatty and Liao (2011). We label this loan loss policy as *HighR2* in our tables.

Recall that one of our important premises is that natural disasters will increase demand for loans. If this premise is correct and treated banks attempt to meet this demand, then we expect β_1 to be positive. We examine this conjecture first.

If this conjecture is supported, we can analyse how banks were able to achieve the loan growth. If meeting the increase in demand is impossible for some banks because their capital is too low, we expect the coefficient β_4 to be positive. (In other words, a positive estimate of β_4 is an indication that there is a capital crunch during the post disaster period). Stated differently, banks that enter disaster periods with greater regulatory capital will find it easier to respond to loan demands. This is illustrated in Figure 1 and Figure 2. Further if growth in lending is facilitated by loan loss policies, then we would also expect that the growth in loans is related to our loan loss policy, perhaps independently of capital, β_2. In other words, our understanding of regulator positions regarding loan loss policies is that banks with more conservative (timely) loan loss policies in the pre-disaster periods should have higher growth in loans during the disaster period. Finally, we re-estimate this regression for big versus for small banks. Big banks may be less constrained on capital because they might be public with easier access to new capital. Hence, the importance of Tier 1 capital and loan loss policies might vary based on bank size.

Similar to prior research, we will define small banks as those with assets less than $500 million. One somewhat controversial result in Beatty and Liao (2011) is that the relation between provisioning and lending seems only to hold for banks with assets greater than $500 million. Beatty and Liao point to changes in regulation which made it more difficult for large banks to assume they were too big to fail. However, while this might explain an increased relation between the hypothesized variables for larger banks, it does not explain why the results do not hold for smaller banks.(This point is made by Acharya and Ryan (2016)). Our sample, which uses call report data, measuring subsidiary and independent bank income statements and balance sheets, comprises more small banks and private banks, than does prior research.

Conceptually, we intend to address the issues raised by Acharya and Ryan (2016) by isolating shifts in demand for loans for specific banks, using the event-dated, locational impacts of natural disasters to separate a treated sample of banks (those exposed to disasters) from a control sample of banks (those not exposed), aligned in event time. We are assuming that the destruction of property that occurs when natural disasters occur, leads to fresh demand from local individuals and business for financing to re–build.[15] Our regression model is very similar to Beatty and Liao (2011) Table 1, except that our post crisis period dummy separates a before versus after period and isolated treated banks from control banks over the same time horizon. In addition, we have considerably more cross-temporal variation in the periods that represent crisis periods.

[15]Coincidentally, Cortés and Strahan (2017) use natural disasters in a similar manner to this reasoning and match natural disasters to loan origination in counties. Cortés and Strahan (2017) assume that natural disasters are good indicators of a shifting up in the demand for loans. Their main interest is to document how connections between banks (e.g., banks that are located nearby and either are, or are not, part of the same bank holding company) impact the servicing of increased loan demand that accompanies a disaster.

4 Data and Descriptive Statistics

4.1 Sample Selection

We use quarterly data covering all banks operating in the United States between 1994$Q1$ – 2017$Q4$. Bank's financial information is from the Bank's Reports of Condition and Income (the "call reports") submitted to the Federal Deposit Insurance Corporation (FDIC). We control for merger effects by excluding observations when the quarterly growth rate of bank's total assets exceeds a 10% threshold, and when the quarterly growth rate of bank loans exceeds 15% threshold (see for e.g., Gatev and Strahan, 2006; Acharya and Mora, 2015). We also require that sample banks to have at least \$100 million in assets, and at least \$1 million in total loans. As described in Table 1, the above selection process produces $407,206$ bank year observations.

We collect data on natural disasters in the US from Spatial Hazard Events and Losses Database for the United States (SHELDUS). SHELDUS is a county–level disaster and hazard database with different natural hazard events, which include thunderstorms, hurricanes, floods, wild–fires, and tornadoes. For each event, the database includes the beginning date, location (county and state), property losses, crop losses, injuries, and fatalities that affected each county. The data are derived from several sources, including the National Climatic Data Center's monthly storm data publications. Following Cortés and Strahan (2017), we identify disasters that the governor declares "state of emergency" with a formal request for funds from the Federal Emergency Management Agency (FEMA), and include the following seven-types of disasters: coastal, wildfire, earthquake, flooding, hurricane, severe storm, and tornado. To ensure that the disaster causes a significant impact to the local economy, we drop disasters with property damage less than \$$50,000$.

We obtain bank location information from the Summary of Deposit (SOD) database provided by the FDIC. This dataset contains geographic information on all branches of depository institutions, including street address, state, ZIP, and county. We aggregate the underlying bank-branch data to the bank-county level. We combine the SOD data and SHELDUS data and identify banks affected by disaster in a particular quarter based on if it operates in a county affected by a disaster.

We also collect quarterly macro-economic information based on the state of the head quarters of the banks. The state–level unemployment rates are from the Bureau of Labor Statistics, the state–level GDP are from the Bureau of Economic Analysis (BEA). The state level housing price index are from the Federal House Financing Agency (FHFA).

4.2 Selecting Comparison Group

A key empirical challenge in our research question is finding an appropriate comparison group for banks that are hit by natural disasters (treated banks). Specifically, the process should ensure that banks that experienced disasters are comparable to banks that operate in the non-disaster area. We use a matching sampling procedure to identify the comparison group of banks that have lagged characteristics similar to the banks in our treatment sample. We implement the propensity–score matched sampling procedure as discussed in (Rosenbaum and Rubin, 1985; Imbens and Rubin, 2015). For each treated bank, we select a control bank from the comparison group of banks, which were not affected by disasters, based on the propensity score calculated from banks characteristics all measured at one–quarter lag relative to the disaster event.[16] We also require the potential matches to have no disaster in the most recent eight quarters. Banks characteristics used for the propensity score calculation include: Size, Deposit, Loan, Homogeneous Loan(%), Head quarter state GDP. We also require exact matches on whether banks are part of a larger holding companies. We implement a one–to–one matching with replacement for control group.

Our matching procedure yields a sample of treatment and control with all covariates balanced at the 1% significance level. For the successfully matched pairs, we include four–quarters before and four–quarters after the disaster period (including the disaster quarter) to create our panel sample. As in Table 1, the final sample include $186,559$ bank–quarter observations, which include $19,911$ bank–quarters affected by disasters.

[16] See Jaravel et al. (2018); Jäger and Heining (2019) for discussion on empirical challenges to difference-in-differences in event study setting.

4.3 Descriptive Statistics

Table 2 Panel A reports descriptive statistics of variables used in our analysis. [17] The mean size of sample banks is \$374 million ($=e^{5.925}$) in total assets, while the median size is \$276 million. A significant portion of sample bank assets are in their loan portfolios. The mean banks' loan share is 66% of its assets, with a standard deviation of 14. Sample banks have a significant portion of their loans in real estate (73.4%) with a bulk of it – 37.04% – in residential real estate suggesting their exposure to catastrophes that destroy properties.

The mean LLP to loan ratio of our sample banks is 0.12, with a standard deviation in the 0.24. The mean non–performing loan to total loans in our sample period is 1.98%, with a standard deviation of 2.70. This suggests there is significant variation in terms of the quality of loans across our sample, allowing us to identify differential responses to disasters.

A key part of our research design is built on the assumption that large banks and small banks located in the same geographical area, having similar business models and loan compositions, react similarly to disasters, and sudden increase in credit demand. In Panel B of Table 2, we show descriptive statistics separately for large and small banks. Not surprisingly, the average size of large banks (1.51 billion) is substantially greater than the average size of small banks (206.34 million).

While large and small banks may appear similar, their *t*– statistics verify that the two populations differ on almost every characteristics reported in the Table. Large banks hold an average of 72.54% of their total loans in real estate, while the smaller banks are little more exposed holding 73.73%. Nevertheless, the median real estate exposure for large banks is greater than those of small banks. Large banks have relatively higher percentage of Commercial and Industrial Loans, and Consumer loans holding 14.64% and 7.91%, respectively. Small banks hold 13.14% and 7.7% in these categories. Small banks rely more on deposits as a source of funding than large banks.

Despite the differences in loan compositions and funding, the quality of the loan portfolios between large and small banks do not differ substantially. The average non-performing loans of

[17] Appendix table Table A.1 describes the variable construction from call report items.

large banks and small banks are 2.04% and 1.96%, respectively. The LLP ratios are similar between large and small banks. Smaller banks have higher Tier 1 capital ratios than do larger banks.

In Table 3, we report the frequency of disasters from the SHELDUS database by year. Specifically, we report the number of unique–counties that were affected by disaster types. Note that SHELDUS can classify one disaster across multiple categories. We follow Cortés and Strahan (2017) and identify the following disaster types: 1) Coastal, 2) Earthquake 3) Flooding, 4) Hurricane/Tropical Storm, 5) Severe Storm/Thunder Storm, 6) Tornado, and 7) Wildfire. The "Total" column refers to the number of unique counties that experience any form of disaster. The number of counties affected by disasters during the years 1994–2000 is 2109, while the number during the years 2001–2007 is 2687. During the last decade between 2008 – 2017, the number of counties subject to disasters is 3449. These suggest that natural disasters have been increasingly trend in the counties that they destruct, which signifies the importance of our result question. In Table 2, the mean property damage by our sample disasters is $122 million.

5 Results

5.1 How are Banks' Loan Loss Provisions Affected by Disasters?

We begin by examining the impact of disasters on loan loss provisions in Table 4 which reports, for the full sample, the results of estimating Equation (3.1), reporting the relation between quarterly loan loss provisions and quarterly changes in non-performing loans. In addition, we control for beginning period bank Size, loan growth, Δ*Loan*, earnings before loan loss provisions and taxes *EBP*, as well as the composition of the loan portfolio residential real estate, *Resid'l RE Loan*; commercial loans, *Comm'l & Indus'l Loan* , and commercial real estate Loans *Comm'l RE Loan*). This model allows the average level of loan loss provisions to shift during disaster periods through the coefficient on *Shock* $\times$ *Post*. In column (1), we report results that include that only include *Shock* $\times$ *Post*. The coefficient is positive and significant, suggesting that disasters increase loan loss provisions on average.

In column (2), we report the results conditioning on bank characteristics. The coefficient of *Shock* × *Post* is negative and significant. In column (3), we repeat the analysis of column (2), but include bank–fixed effects, to control for for un-modelled, bank-specific influences on loan loss provisions that are constant over time. Our preferred model includes state–time fixed effects to control for factors that vary by state and time.

First, note that the regression weights on changes in non-performing loans, size, loan growth, and on residential real estate, do not seem to be very sensitive to the inclusion of various forms of fixed effects. In columns that contain changes in non-performing loans, the estimated regression weights and significance levels are very similar, with relatively small standard errors. For example, the coefficient on future changes in non-performing loans is 0.0211 and 0.0102 in columns 2 and 3 respectively and all are reliably different from zero using standard statistical confidence levels. These estimates suggest that for every dollar change in management's expectation of next periods non-performing loans scaled by loans, an additional ten to twenty cents per loan outstanding is added to the loan loss provision. On average, the weights on lagged changes in non-performing loans (at $t-1$ and $t-2$) have slightly higher weights (e.g., 0.0370 and 0.0329 in column 5) versus the weights on current and future changes in non-performing loans (0.0289 and 0.0102 in the same column). This suggests that on average bank-managers place greater default rates on past changes in non-performing loans than they do on current and expected changes in non–performing loans.

The coefficient of *Shock* × *Post* in column (3) is not statistically significant in any of the estimations, suggesting there is no average difference in loan losses between treated and control banks in the post disaster period. In columns (4) and (5), we repeat analysis in column (3) by splitting our full sample in to sub samples of large banks (defined as those with assets $>$ 500 million) and small. The coefficient of *Shock* × *Post* seems to suggest that the insignificance in the full sample is driven by the offsetting effect between small and large banks as reported in columns

(4) and (5). In Appendix Table A.2, we repeat the analysis in column (3) by including bank and quarter fixed effects to show that the average effect of *Shock* × *Post* in column is robust to other specifications.

While the insignificant coefficient of *Shock* × *Post* in column (3) may seem to imply that disasters have no impact on loan loss provisions, Panel B of Table 4 shows that the process by which loan loss provisions are set, shifts in the four quarters encompassing the disaster. In this panel we allow the coefficients on future, current and lagged changes in non-performing loans to change. In addition, we allow the coefficients on earnings before loan loss provisions and on Tier 1 capital to shift. The incremental coefficient on future non-performing loan changes is 0.0047 in column 1 and this, when added to the base coefficient on future non-performing loans of 0.0054 indicates that there is close to an 87% (.0047/.0054) increase management's assessment of default risk due to future changes in non-performing loans, during the four quarters that include and follow a disaster. This increase is relative to the weight on non-performing loans as determined by before the disaster and by unaffected control banks. The weights on current, one and two period lagged changes in non-performing loans exhibit increases of 48.3%, 39.7%, and 8.5% (but this last estimate is not statistically significant). Hence shortly after a disaster, the average treated bank places more emphasis on forecasts of future changes in default risk, in setting loan loss provisions and, management also increases the default risk estimates associated with current and lagged indicators, but at somewhat lower rates of increases.

Table 4, panel B also reports how loan loss provisions are related to pre-determined Tier 1 capital ratios and to pre-provision earnings. The base coefficient on the Tier 1 ratio lies between −0.0016 and −0.0041, suggesting that banks with larger Tier 1 capital are less likely to add to the provision for loan losses. A positive relation between these two variables would be consistent with the manipulation of loan loss provisions to manage Tier 1 capital. The negative relation we document likely indicates that high Tier 1 capital banks choose to invest in safer loans. Note that the interaction of the disaster period indicator and Tier 1 capital is also negative. This means that that high capital banks add even less to their loan loss provisions in the post disaster periods; they are perhaps very conservative in taking on risky loans. The base relationship between earnings before provisions (scaled by assets), and loan loss provisions (scaled by loans) is positive and significant (e.g., the point estimate is 0.2660 in column 1). This is consistent with bank's choosing to smooth their earnings via the loan loss provision. In Table 4, we find no incremental smoothing on average in the four quarters following the disaster, (i.e., the coefficient on our shock term interacted with earnings before provisions is 0.0033 and this is statistically insignificant).

We suspect that the loan loss provisioning practices differ for large banks versus smaller banks. For example, larger banks are more likely to have sophisticated modelling technologies available for updating loan loss provisions (Bhat et al., 2018). And large bank sample is sample like is more dominated by publicly traded, SEC regulated firms; hence their loan loss provisioning tactics can reflect the demands of the SEC or shareholders. [18]

Table 5 examines whether disasters differentially affect the loan loss provisioning habits of large versus small banks. The table suggests that small banks seem to have a large weight on future changes in non-performing loans (the coefficient is 0.0066), but there is no change in this weighting during the disaster period. In contrast, the larger banks show an insignificant base coefficient on future non-performing loans in column 3 (the estimate is -0.0012) but, once a disaster occurs, this variable receives a positive weight of 0.0123, which is statistically significant). Hence, small banks appear to have more forward-looking loan loss provisions at all times, while bigger banks appear to save this until they encounter a disaster.

One explanation could be that this reflects a different loan composition for small versus large banks. Ryan and Keeley (2013) argue for the case in difference in portfolio composition of large versus small banks. Panel C, which further separates banks based on loan composition, suggests this explanation is not valid.

[18] For example, Craig et al. (2009) argues that publicly-traded banks are more likely to have conservative earnings. Their research supports this conjecture; they confirm that loan loss provisions are a mechanism that form a part of this conservatism.

Second, note that once small and large banks have been separated, the difference in difference average effect of a disasters is positive for large banks but is negative for small banks (column 3 versus column 1, the coefficient on $Shock \times Post$) This is consistent with large banks increasing the conservatism of their loan loss provisions, over and above the amount expected, based on loan loss indicators, during disaster periods. Whereas large banks show a greater weighting on future changes in non-performing loans (0.0123 in column 3), the incremental weighting on this variable is indistinguishable from zero for smaller banks. (However, small banks place a bigger weight on current and on one period, lagged changes in non-performing loans during disaster periods). Finally there is weak evidence that large banks engage in more smoothing during disaster periods, i.e., the coefficient on the interaction of our disaster dummy variable with earnings is positive and marginally significant.

In Panel B of Table 5, we examine whether loan loss provisioning behavior differs in the fourth quarter, when the audit is being completed, versus in the remaining three quarters (See for e.g., Liu et al., 1997). Whereas in panel A it appears that small banks do not increase their incorporation of future changes in non-performing loans after disasters, Panel B suggests that they do so, but only in the fourth quarter. This results is only significant at the 10% level, two-tailed significance. Large banks appear to increase their weighting on forward looking information in the first three quarters of the year, but not in the fourth quarter. However, in the fourth quarter, this is where we find there is an increase in detected earnings smoothing.

Taken together, the results in Table 4 and Table 5 suggest first that disasters are associated, for big banks, with an increased incorporation of forward–looking information into their loan loss provisions. This is important because prior research suggests that the incorporation of future information in loan loss provisions is an indicator of high accounting quality. To the extent that the weighting on future information is simply a by-product of a bank being located in a disaster prone area, this finding casts some doubt on the idea that the weight on future changes in non-performing loans is a reliable indicator accounting quality. Interestingly, small banks appear to weight forward looking information in all quarters, regardless of whether there has been a disaster. Some would argue this means small banks have higher-quality loan loss provisions. Given the demonstrated difference in loan loss provisioning models for big versus small banks, we estimate loan loss provisioning policies (for our investigation of how banks respond to loan shocks) using samples that are stratified on size.

5.1.1 Do Banks that are more Exposed to Disasters Learn from Experience?

One concern with our prior analysis is the treatment of disaster events as a fully exogenous event for banks. Since there are some geographic areas in the US that are repeatedly subject to disasters (such as Florida, Louisiana), these events might not be fully unanticipated. We posit that the magnitude and the timing of the disaster may be the two parameters that are fully exogenous. Therefore, banks subject to multiple disasters across time, might learn from their prior disaster experience, which should reflect in their provisioning policies.

In Table 6, we formally investigate whether banks that are exposed to multiple disasters, adapt their loan loss provisioning policies. Specifically, we examine whether banks with more frequent disasters are more forward looking in their loan provision estimates. Given the scope, we solely focus on banks that experience disasters (treated banks) and do not include our control banks in the analysis in Table 6. We include a variable *CumDisaster*, which is the banks' disaster experience measured as the number of disasters the bank experienced in the past. We interact the coefficients on loan loss indicators with *CumDisaster*, and examine whether the weights on loan loss indicators are higher for banks that experience more disasters. In addition, we expect banks to react differently to more recent disaster experience, relative to ones in longer periods in history.

In columns (1) – (3) of Table 6, we consider the entire history of disaster experience for bank. In columns (4) – (6), we focus only on disaster experience in the past three–years. In columns (1) and (4), for the full sample, we find evidence that banks exposed to multiple disasters indeed apply larger weights on future changes to non–performing loans. Small banks (column (3)) weigh their entire history, while large banks (column (5)) weigh based on their recent past. Across all our columns, we find that banks subject to multiple disasters cause banks to apply larger weights on their current changes in non–performing loans. The coefficient of CumDisaster × Δ Non-Perf. Assets_{t+1} in column (4) is larger than that of column (1) suggesting banks assign larger weights to their recent past, than their entire history of disasters. The results in Table 6 caution us against the idea that disasters can be treated as fully exogenous events, particularly when we examine the relation between loan loss policies and capital, versus growth in lending during disaster periods.

5.2 Do Banks with Greater (Less) Conservatism and Timeliness in Provisioning Respond More to Shifts in Demand for Loans?

Table 7 and Table 8 show the estimates of Equation (3.3). Recall this regression provides evidence about whether pre–crisis provisioning policies correlate to a more responsive reaction to the increased loan demand that we assume accompanies natural disasters. The regression employs two different loan-loss policy dummy variables *HighRES12* versus *HighR2*. As described in Section 3.2, *HighRES12* indicates banks with more conservative loan loss provisioning policies, based on the computation of rolling average residuals from Equation (3.1). *HighR2* banks place relatively more weight on current and future changes in non–performing loans, than do other banks. This measure of "timeliness" has been verified to be related to bank's ability to lend during economic–wide crisis periods in Beatty and Liao (2011), and is correlated with more discipline demonstrated over bank risk taking in Bushman and Williams (2012).

Turning now to the results, Table 7 panel A relates bank loan growth to determinants, i.e., Equation (3.3), but excluding the loan loss policy variables. We do this in part to verify whether, as we have presumed, demand for loans increases in the aftermath of disasters. Panel A supports this conjecture, as evidenced by the positive and statistically significant coefficient on *Shock* × *Post*. Note that both small and large banks exhibit growth in lending during disaster periods. In addition, this panel suggests that loan growth increases in Tier 1 capital and when there is greater earnings before loan loss provisions. Loan growth is greater for banks with a greater portfolio of commercial loans and it is lower if banks show a lagged increase in non-performing assets.

Panel B of Table 7 explores the channels by which banks achieve post–disaster loan growth, focusing on regulatory capital and provisioning conservatism. The first three columns of this panel allow for disasters to impact loan growth through a shift in intercept for *conservative* banks (*HighRES12*), for the post disaster period, *Shock* × *Post*, and through the interaction of these two factors. In the first row of this table, one notices that loan growth is lower on average, among the most conservative banks (the coefficients on *HighRES12* are negative and statistically significant). In the second row of this Table (first three columns) we confirm that growth in lending is greater for banks in post disaster periods, in comparison to matched unaffected control banks. In the third row, in column 2, for small banks, the reaction to the disaster is greater if loan loss provisions have been conservative before the disaster. This is indicated by the positive and significant coefficient on *Shock* × *Post* × *HighRES12*. In other words, among the small bank sample there is greater loan growth in the post disaster period for small banks that had more ample loan loss provisions in the periods preceding disasters. In contrast, the neighbouring coefficient in column 3 for big banks, is insignificant, suggesting that this link between loan loss policies and lending is not important for post disaster periods.

Columns (4) through (6) expand the potential influences on loan growth to Tier 1 capital. If some banks face increasingly tight capital constraints following disasters, we expect an increased weighting on Tier 1 capital in predicting loan growth, after disasters; this can be detected by inspecting the coefficient on the interactions of *Shock* × *Post* with accounting policies and Tier 1 capital. To repeat, we report results separately for small versus large banks because big banks tend to have more publicly traded holding companies, and likely have easier access to capital so they are less likely to have exhibit binding capital constraints in post disaster periods. This distinction is manifested by the positive and significant coefficient for *Shock* × *Post* × *Tier1 Ratio* for small banks, (versus the negative analogue for big banks). The positive coefficient on regulatory capital, post disaster, for small banks is consistent with some small banks becoming more capital constrained during crisis periods. Stated differently, it is small banks with greater Tier 1 capital that are able to respond the most to increased loan demand in the post-crisis period. Note that in column 5, the third row, the positive influence of loan loss provisioning conservatism on post disaster lending, is no longer evident (i.e., the coefficient on *Shock* × *Post* $\times HighRES12$ is not statistically significant, in contrast to in column 2). Hence, any influence of loan loss conservatism on post-disaster lending for small banks is apparently confounded by those banks also holding higher Tier 1 capital.

The inclusion of *Shock* × *Post* × *Tier1 Ratio* in column 6 for big banks yields a perversely negative influence of Tier 1 capital on growth in lending. Thus, the most aggressive loan growth in big banks during disaster periods occurs for those with lower Tier 1 capital. This negative coefficient suggests that large banks are not facing capital crunches during crisis periods. Given the lack of evidence of a credit crunch in the post disaster period for large banks, this suggests that looking for evidence of a relation between loan loss policies and loan growth is not likely to be meaningful.[19] Similar to column 3, the coefficient on *Shock* × *Post* is positive and significant in column six for the big bank sample. This suggests that big banks respond positively to the shock to loan demand, regardless of their Tier 1 capital.

Finally whether it be big or small banks, during *non-disaster periods*, the results suggest loan growth is higher, when loan loss provisioning and Tier 1 capital are higher–indicated by the positive coefficient on the *Tier 1 capital* × *HighRES12* variable.[20]

Panel C repeats the analysis in Panel B, but the construct for loan loss provisioning quality is now *timeliness* rather than *conservatism*. Again, *timeliness* is captured by the degree to which a loan-loss provisioning model relies on time t and time t+1 changes in non-performing loans. As shown, this variable (denoted *HighR2*) does not have a positive impact on loan growth (in some cases

[19] Consistent with this interpretation of our results, Beatty and Liao (2011) focus attention solely on big banks. This focus is due to the lack of evidence that small banks face capital crunches during the recessionary periods.

[20] Beatty and Liao (2011) examine if banks that engender high quality provisioning policies are less reliant on Tier 1 capital during economic downturns. This would manifest in our research design as a negative coefficient on the interaction of our shock dummy variable with *HighRES12* × *Tier 1 Ratio*. We find that this coefficient is not negative, it is zero or positive, in the second to last row of Panel B.

the influence is estimated to be negative). This contrasts to the results in Beatty and Liao (2011) where timeliness appears to facilitate lending for large, publicly traded entities during extreme and general economic downturns. In short, the results documented by this prior paper in the context of general economic downturns (for big banks), does not generalize to either big or small banks during localized downturns that are the result of disasters. While we believe our research design helps to control for potential omitted variables relative to this prior study, we obviously would not be able to refute their findings, which are based on consolidated bank holding companies and focus on periods with perhaps greater stresses for these particular entities, than occur due to natural disasters.

Table 7 presents our data analysis in a format that is very similar to Beatty and Liao (2011), thereby allowing for direct comparisons for our sample versus in the prior published work. For ease with interpretation, in Table 8 we partition the samples into high and low provisioning banks. (In this table, the dependent variable is again, loan growth). In column 1 for the full sample, this table suggests that lending growth occurs for banks with a correspondence between high provisions and high tier 1 capital. Column 2 shows that for small banks loan growth occurs in the post disaster period for high provision banks with high tier 1 capital. This evidence is consistent with the idea that high provisioning policies lead banks to raise more capital. However, the result is also consistent with the slightly different interpretation that high provisioning policy banks are just more conservative. That is, the relationship between capital and provision policies might well be the consequence of a third, omitted variable, which is management conservatism. [21]

Turning now to large banks, Table 8 shows that for this subsample, loan growth is higher for low provision banks in the post disaster period. As we noted for Table 7, panel B, this evidence is inconsistent with regulator claims that ample provisioning assists in lending during crisis periods. However, as mentioned with respect to Table 7 , our conjecture is that big banks are not constrained on capital to the same degree as small banks in the aftermath of disasters.

[21] Some readers may wonder why there is not an additional Table, showing results with partitions based on *HighR2*. We have suppressed the equivalent analysis based on *HighR2* because it yields no additional insights to Table 7 Panel C.

6 Conclusions

This paper traces disasters such as wild fires, floods and hurricanes to banks that reside in counties that are impacted by these disasters. We presume that these banks are subject to a localized increase in the demand for loans, and possibly a simultaneous decrease in the supply of loans due to the impact of increased credit risk on capital ratios.

We use our setting to examine two questions. This first is how do banks' loan loss provisioning practices change when their operations and customers, become exposed to disasters? This question is of interest because disasters give banks the license to engage in more forward-looking loan loss provisions, in advance of the cash flow triggering events that typically accompany a loan loss provision. Prior research often interprets a banks' reliance on forecasted changes in credit risk, as an indication that the bank has used high quality provisioning methods. We document that disasters are associated with an increased use of forward-looking information, particularly for larger banks. But we emphasize that in this instance, the increased weight on forward-looking information does not necessarily correspond to higher quality provisions. Rather, we think the reliance on forward looking information in this instance is endemic to the type of triggering event, and does not mean that managers have improved provisioning quality. This insight contributes to work by Bhat et al. (2016) and Bhat et al. (2018), which are two papers that present evidence that standard measures of loan loss quality and their relation to firm results are sometimes a coincidental outcome of un-modelled features of the bank's operations, such as sophistication of data analytics and loan composition.

Our second question asks whether banks' loan loss provisioning attitudes or policies help to alleviate the constraints imposed on banks when both demand shifts out, and supply shifts out. We see natural disasters as creating isolated crisis periods (similar to a recession) that hit different banks at different times. These events have the potential to create constraints on lending aka 'capital crunch' periods. In as much as regulators and economists have asserted that loan loss provisioning methods exacerbate cyclical downturns, we believe that that this setting allows us to test the links between loan loss provisioning qualities, and capital constraints. Prior research finds support for regulator assertions that more timely (meaning more forward looking) loan loss provisions, alleviate capital constraints (e.g., Beatty and Liao (2011)).

In this paper we propose to re-examine these ideas, but we employ a difference in difference research design that uses the impact of natural disasters to identify banks subject to demand shifts. In Figure 1 and Figure 2, we illustrate how a difference in difference design can be used to sharpen inferences regarding this hypothesis. We measure loan loss conservatism as the error term from a regression of loan loss provisions on credit loss indicators and other controls. Those banks with the most positive residuals are classified as conservative provisioning banks. We measure a second construct (loan timeliness) as the incremental r-squared from a regression that includes current and forward-looking loss indicators versus a regression that omits these terms. We then regress growth in loans before, versus after, a disaster and we allow this growth to be impacted by bank's loan loss accounting policies. Our results find no evidence that *timeliness* of loan loss provisions is helpful in alleviating capital constraints. We find some evidence that small banks with more conservative loan loss policies in pre-disaster periods, exhibit greater loan growth following disasters (relative to control banks that are not impacted by disasters). However, this link between loan loss policies and lending is co-mingled with the impact on lending of a bank's Tier 1 capital ratio. The evidence we find for loan loss accounting policies impacting growth in lending for small banks, rather than big banks, contrasts to work by Beatty and Liao (2011) which found results consistent with regulator claims for loan loss timeliness, for big banks, but not for small banks.

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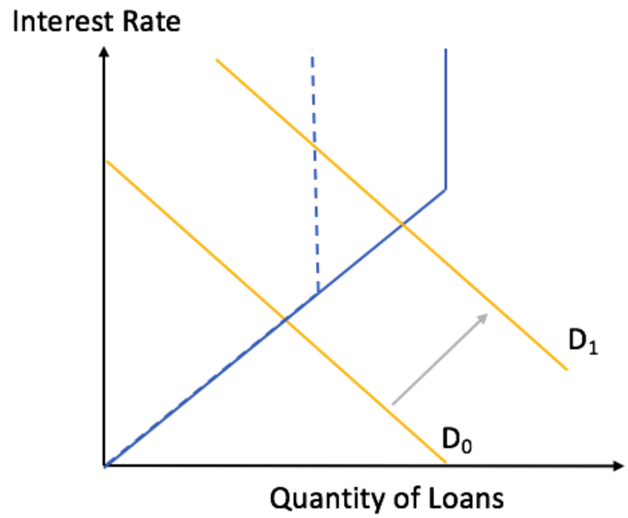
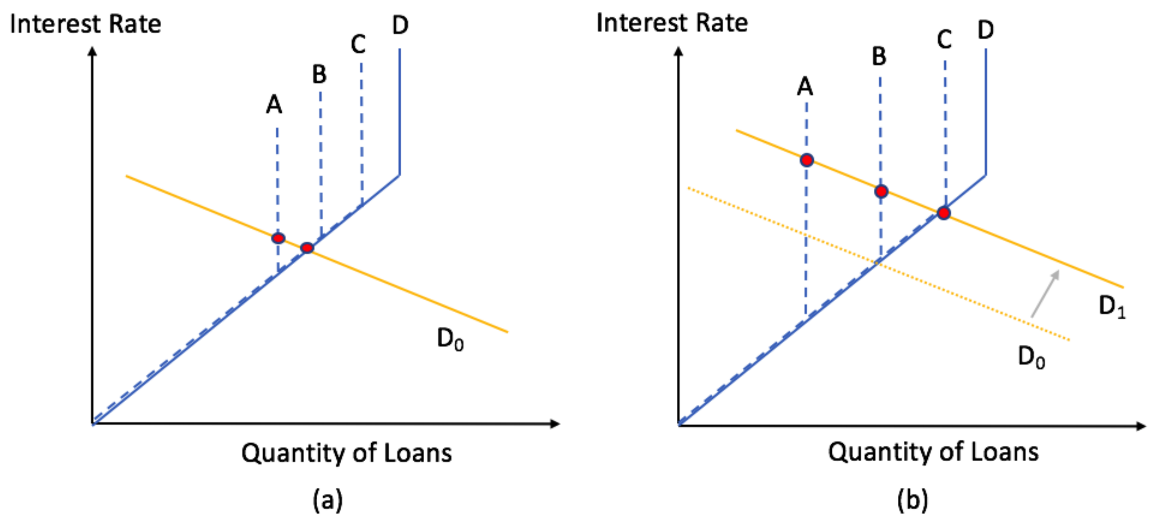
FIGURE 1: Effect of LLP on Loan Lending during Disaster



This figure shows the loan change during the disaster. In this figure, the natural disaster is modelled as an exogenous shock that shifts the demand from D_0 to D_1. The blue dashed line is the supply curve of the bank with low loan loss provision, and the blue solid line is the supply curve of the bank with high loan loss provision. Loan loss provision determines the kink from which bank's further lending is restricted. For low provision banks, the kink is lower because they don't have enough provision ready to absorb the loan loss caused by the disaster; thus they are more likely to be tangent on their tier 1 capital constraint. So their ability to respond to the increased demand will be restricted.

FIGURE 2: Comparison of Effect of LLP on Loan Lending Between Disaster and Non-Disaster Period



This figure shows the change of the relation between loan loss provision and banks' lending activity before and after the disaster. From bank A to bank D, banks' (pre-disaster period) loan loss provision(LLP) increases monotonically. (a) shows banks' lending activity during non-disaster period: bank B, C, and D have the same lending amount as they are not constrained by the tier 1 capital constraint, while bank A has a lower level of lending amount because of the capital constraint. (b) shows the lending activity during the disaster period The disaster not only shifts up the demand of loans but also shifts banks' capital constraints towards the left. The capital constraints shift more if the bank has lower (pre-disaster period) LLP to absorb the losses caused by the disaster. Thus, banks with higher LLP will respond more to the increased demand. From (a) to (b), the positive correlation between the loan loss provision and banks' lending become stronger.

TABLE 1: This table describes the sample selection process used in the paper.

Call Report Data from 1994 Q1 to 2017 Q4	864,033
merge with FDIC deposit-weighted SHELDUS Disaster	835,691
drop if asset < \$100 million	440,449
drop if total loans < \$1 million	438,892
drop if asset growth > 10%	413,871
drop if loan change > 15%	410,253
drop if missing key variables	407,206
propensity score matching*	186,558

*1-to-1 matching with replacement

TABLE 2: This table reports descriptive statistics of the sample used in the empirical analysis. Panel A presents descriptive statistics for the full sample. Panel B presents summary statistics separately for small and large banks in the sample. *Ln(Total Asset)* is the natural logarithm of total assets. *LLP* is loan loss provision, scaled by lagged total loans. *Deposit* is deposits, scaled total assets. *Interest Income* is interest incomes, scaled by total assets. *EBP* is earnings before loan loss provisions and taxes, scaled by lagged total assets. *Tier1 Ratio* is the Tier 1 capital ratio of the bank. *Loan* is the total loans, scaled by assets. Δ *Loan* is the change in loans from last quarter to current quarter, scaled by loans in last quarter. *Resid'l RE Loan* is the ratio of residential real estate loans to total loans. *Comm'l RE Loan* is the ratio of commercial real estate loans to total loans. *Comm'l & Indus'l Loan* is the ratio of commerical and industrial loans to total loans. Δ *Non-Performing Assets* is banks' Non-performing Assets scaled by lagged total loans. *PropertyDamage* is the average property damage experienced by a bank. Δ *GDP* is the change in GDP of the head-quarter state of the bank. Δ *Unemployment* is the change in unemployment of the head–quarter state of the bank. *House Index* is the housing price at the head–quarter state of the bank.

Panel A

	N	Mean	SD	Min	P25	Median	P75	Max
Disaster								
Dummy_4QTR	186,558	0.343	0.475	0.000	0.000	0.000	1.000	1.000
PropertyDamage_4QTR	186,558	122.1	769.2	0.0	0.0	0.0	0.0	6,748.7
Bank								
Ln(Total Asset)	186,558	5.925	1.141	4.621	5.096	5.620	6.400	10.205
Tier1 Ratio	176,306	14.738	6.284	7.190	10.790	12.900	16.430	46.390
LLP(%)	186,558	0.119	0.236	-0.143	0.013	0.053	0.117	1.615
Loan	186,558	0.661	0.143	0.202	0.579	0.679	0.764	0.925
Non-Perf. Assets(%)	186,558	1.985	2.701	0.000	0.453	1.061	2.316	16.218
Δ Non-Perf. Assets(%)	186,558	0.026	0.636	-2.166	-0.170	-0.004	0.160	2.846
Interest Income	186,558	0.035	0.018	0.008	0.019	0.033	0.047	0.081
Deposit	186,558	0.817	0.085	0.396	0.782	0.838	0.877	0.928
EBP(%)	186,558	0.317	0.200	-0.341	0.212	0.307	0.406	1.361
Comm'l & Indus'l Loan(%)	186,558	13.586	10.421	0.000	6.219	11.788	18.646	56.102
Real Estate Loan(%)	186,558	73.373	18.405	0.268	63.115	76.025	86.915	100.000
Consumer Loan(%)	186,558	7.756	10.144	0.000	1.587	4.354	9.983	72.879
Comm'l RE Loan(%)	167,750	0.262	0.869	0.000	0.000	0.000	0.000	6.023
Resid'l RE Loan(%)	186,558	37.045	22.738	0.020	20.690	31.831	48.425	97.555
Δ Loan_4QTR	73,791	0.046	0.095	-0.220	-0.009	0.047	0.100	0.345
State								
Δ GDP	4,998	6.17	11.59	-61.46	0.82	2.71	7.39	119.47
Δ Unemployment	4,998	-0.02	0.31	-4.77	-0.20	-0.07	0.07	2.63
House Index	4,998	186.16	58.60	82.46	143.18	184.19	215.82	564.62

*Property Damage and Δ GDP are in thousands.

Panel B

	Small			Large				
	Mean	Median	SD	Mean	Median	SD	Diff-in-means	t
Disaster								
Dummy_4QTR	0.313	0.00	0.464	0.416	0.00	0.493	-0.103***	(-42.01)
PropertyDamage_4QTR	80.12	0.00	604.10	220.64	0.00	1053.38	-140.53***	(-29.50)
Bank								
Ln(Total Asset)	5.331	5.301	0.443	7.319	6.958	1.061	-1.988***	(-426.85)
LLP(%)	0.109	0.049	0.219	0.145	0.062	0.270	-0.036***	(-27.84)
Allowance(%)	1.422	1.288	0.722	1.509	1.337	0.811	-0.0874***	(-22.00)
Loan	0.656	0.674	0.144	0.673	0.690	0.139	-0.017***	(-23.39)
Non-Perf. Assets(%)	1.962	1.053	2.691	2.041	1.080	2.723	-0.079***	(-5.75)
Δ Non-Perf. Assets(%)	0.027	-0.007	0.663	0.024	0.178	0.566	0.003	(0.99)
Interest Income	0.035	0.034	0.018	0.032	0.031	0.018	0.003***	(29.65)
Deposit	0.834	0.850	0.071	0.778	0.801	0.101	0.057***	(119.97)
EBP(%)	0.311	0.303	0.1911	0.332	0.313	0.219	-0.0210***	(-19.71)
Tier1 Ratio	0.153	13.40	0.065	0.135	11.950	0.056	0.018***	(60.23)
Comm'l & Indus'l Loan(%)	13.139	11.507	9.9151	14.6361	12.604	11.453	-1.4972***	(-26.87)
Consumer Loan(%)	7.691	4.857	9.110	7.907	3.132	12.2309	-0.216***	(-3.74)
Real Estate Loan(%)	73.731	75.840	17.388	72.536	76.473	20.5697	1.195***	(12.01)
Comm'l RE Loan(%)	0.212	0.000	0.828	0.382	0.000	0.9480	-0.170***	(-34.83)
Resid'l RE Loan(%)	37.356	32.121	22.618	36.315	31.208	23.0	1.041***	(8.99)
Observations	130,804			55,754			186,558	
Δ Loans_4QTR	0.0424	0.097	0.0948	0.0570	0.059	0.0958	-0.0146***	(-17.54)
HighRes	0.1936	0.000	0.3951	0.1976	0.000	0.3982	-0.0041	(-1.18)
HighR^2	0.5024	1.000	0.5000	0.4983	0.000	0.5000	0.0041	(0.94)
Observations	56,871			17,381			74,252	

TABLE 3: This table reports the number of counties that were affected by disaster types from SHELDUS database. The Total column shows the number of unique counties that experienced any form of disaster.

Year	Coastal	Earthquake	Flooding	Hurricane/ Tropical Storm	Severe Storm/ Thunder Storm	Tornado	Wildfire	Total
1994	0	1	115	13	34	12	0	149
1995	1	0	178	53	65	29	0	289
1996	5	0	305	62	25	21	4	394
1997	0	0	298	3	20	24	0	313
1998	1	0	362	86	127	112	66	554
1999	0	0	128	105	37	43	8	290
2000	0	0	91	0	25	17	11	120
								2109
2001	3	0	182	21	9	53	0	232
2002	0	0	196	49	22	65	15	306
2003	2	0	281	120	71	119	8	520
2004	0	0	389	121	61	104	3	582
2005	5	0	225	231	52	60	30	492
2006	1	0	152	0	44	64	39	281
2007	0	0	235	0	31	31	8	274
								2687
2008	45	0	389	182	109	147	11	645
2009	0	0	169	0	57	41	5	231
2010	1	0	311	3	59	29	0	342
2011	0	0	366	122	133	185	66	671
2012	4	0	126	60	113	38	6	300
2013	0	0	179	0	26	16	2	205
2014	0	0	99	0	21	16	5	126
2015	0	0	222	1	32	63	2	278
2016	3	0	203	29	8	18	4	232
2017	0	0	207	227	18	25	14	419
								3449

TABLE 4: This table presents the effect of Disaster on LLP. Panel A of this table shows the average effect of disaster on banks' loan loss provisioning. Panel B shows how banks adjust the weight of their non–performing assets on their loan loss provisioning during natural disaster period. The dependent variable is banks' loan loss provisions in the current quarter scaled by lagged total loans. *Shock* is a dummy variable, which is equal to 1 for banks that are affected by a disaster. *Post* is the dummy variable, which is equal to 1 from 0 to 3 quarters after a disaster. *Ln(Total Asset)* is the natural logarithm of total assets. *Tier1 Ratio* is the Tier 1 capital ratio of the bank. *EBP* is earnings before loan loss provisions and taxes. Δ *Loan* is the change in loans from last quarter to current quarter scaled by loans in last quarter. *Residential Real Estate Loan* is the ratio of residential real estate loans to total loans. *Commercial Real Estate Loan* is the ratio of commercial real estate loans to total loans. *Commercial and Industrial Loan* is the ratio of commerical and industrial loans to total loans. Δ *Non-Performing Assets* is banks' Non-performing Assets scaled by lagged total loans.

Panel A

	(1) Full	(2) Full	(3) Full	(4) Small	(5) Large
Shock × Post	0.0000***	-0.0000***	-0.0000	-0.0000***	0.0000**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Ln(Total Asset)$_{t-1}$		0.0001***	0.0002***	0.0003***	0.0002***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
Tier1 Ratio$_{t-1}$		-0.0018***	-0.0017***	-0.0018***	-0.0018***
		(0.0001)	(0.0002)	(0.0002)	(0.0004)
EBP		0.2169***	0.2523***	0.2532***	0.2668***
		(0.0029)	(0.0036)	(0.0044)	(0.0066)
Δ Loan		-0.0106***	-0.0058***	-0.0052***	-0.0063***
		(0.0001)	(0.0001)	(0.0002)	(0.0003)
Resid'l RE Loan		-0.0012***	-0.0007***	-0.0004***	-0.0011***
		(0.0000)	(0.0001)	(0.0001)	(0.0002)
Comm'l & Indus'l Loan		-0.0010***	-0.0002*	0.0002	-0.0010***
		(0.0001)	(0.0001)	(0.0001)	(0.0002)
Comm'l RE Loan		0.0009	-0.0006	-0.0002	-0.0021
		(0.0006)	(0.0008)	(0.0010)	(0.0016)
Δ Non-Perf. Assets$_{t+1}$		0.0211***	0.0102***	0.0090***	0.0066***
		(0.0008)	(0.0007)	(0.0008)	(0.0016)
Δ Non-Perf. Assets		0.0408***	0.0289***	0.0232***	0.0427***
		(0.0009)	(0.0008)	(0.0009)	(0.0017)
Δ Non-Perf. Assets$_{t-1}$		0.0544***	0.0370***	0.0336***	0.0397***
		(0.0009)	(0.0008)	(0.0009)	(0.0016)
Δ Non-Perf. Assets$_{t-2}$		0.0499***	0.0329***	0.0276***	0.0422***
		(0.0009)	(0.0008)	(0.0009)	(0.0016)
Constant	0.0012***	0.0007***	-0.0004***	-0.0009***	-0.0001
	(0.0000)	(0.0000)	(0.0001)	(0.0002)	(0.0003)
Bank FE	No	No	Yes	Yes	Yes
State-Time FE	No	No	Yes	Yes	Yes
Observations	186558	157907	157772	110602	47045
Adjusted R^2	0.00	0.15	0.40	0.35	0.52

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel B

	(1)	(2)	(3)	(4)
	LLP	LLP	LLP	LLP
Shock × Post	-0.0000	-0.0000	0.0001***	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Shock × Post × Δ Non-Perf. Assets$_{t+1}$	0.0047***			0.0045***
	(0.0015)			(0.0015)
Shock × Post × Δ Non-Perf. Assets	0.0102***			0.0100***
	(0.0016)			(0.0016)
Shock × Post × Δ Non-Perf. Assets$_{t-1}$	0.0111***			0.0109***
	(0.0016)			(0.0016)
Shock × Post × Δ Non-Perf. Assets$_{t-2}$	0.0023			0.0021
	(0.0016)			(0.0016)
Shock × Post × Earnings before Provisioning		0.0061		0.0033
		(0.0055)		(0.0055)
Shock × Post × Tier1 Ratio$_{t-1}$			-0.0007***	-0.0006***
			(0.0002)	(0.0002)
Δ Non-Perf. Assets$_{t+1}$	0.0054***	0.0070***	0.0070***	0.0055***
	(0.0009)	(0.0007)	(0.0007)	(0.0009)
Δ Non-Perf. Assets	0.0211***	0.0246***	0.0246***	0.0212***
	(0.0009)	(0.0008)	(0.0008)	(0.0009)
Δ Non-Perf. Assets$_{t-1}$	0.0279***	0.0317***	0.0317***	0.0280***
	(0.0009)	(0.0008)	(0.0008)	(0.0009)
Δ Non-Perf. Assets$_{t-2}$	0.0271***	0.0280***	0.0280***	0.0272***
	(0.0009)	(0.0008)	(0.0008)	(0.0009)
EBP	0.2660***	0.2636***	0.2657***	0.2647***
	(0.0036)	(0.0041)	(0.0036)	(0.0041)
Tier1 Ratio$_{t-1}$	-0.0016***	-0.0016***	-0.0014***	-0.0014***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Ln(Total Asset)$_{t-1}$	0.0003***	0.0003***	0.0003***	0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Δ Loan	-0.0048***	-0.0048***	-0.0048***	-0.0048***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Resid'l RE Loan	-0.0007***	-0.0007***	-0.0007***	-0.0007***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Comm'l & Indus'l Loan	0.0000	0.0000	0.0000	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Comm'l RE Loan	-0.0018**	-0.0018**	-0.0018**	-0.0018**
	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Constant	-0.0006***	-0.0006***	-0.0006***	-0.0006***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Bank FE	Yes	Yes	Yes	Yes
State-Time FE	Yes	Yes	Yes	Yes
Observations	157673	157673	157673	157673
Adjusted R^2	0.44	0.44	0.44	0.44

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

TABLE 5: This table presents the effect of natural disaster on banks' loan loss provisioning for small banks and large banks separately. The size cut–off for small and large banks is $500 million. Panel B shows the different effect of natural disaster on banks loan loss provisioning in the first three–quarters and the forth–quarter. Panel C presents the effect of natural disaster on banks' loan loss provisioning for banks with a relatively high proportion of homogeneous loans and heterogeneous loans separately. Homogeneous loans include residential real estate loans and consumer loans. The dependent variable is banks' loan loss provisions is the current quarter scaled by lagged total loans. *Shock* is a dummy variable, which is equal to 1 for banks that are affected by a disaster. *Post* is the dummy variable, which is equal to 1 from 0 to 3 quarters after a disaster. *Ln(Total Asset)* is the natural logarithm of total assets. *Tier1 Ratio* is the Tier 1 capital ratio of the bank. *EBP* is earnings before loan loss provisions and taxes. Δ *Loan* is the change in loans from last quarter to current quarter scaled by loans in last quarter. *Residential Real Estate Loan* is the ratio of residential real estate loans to total loans. *Commercial Real Estate Loan* is the ratio of commercial real estate loans to total loans. *Commercial and Industrial Loan* is the ratio of commerical and industrial loans to total loans. Δ *Non-Performing Assets* is banks' Non-performing Assets scaled by lagged total loans.

Panel A

	Small		Large	
	(1)	(2)	(3)	(4)
	LLP	LLP	LLP	LLP
Shock × Post	-0.0001***	0.0001	0.0001***	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0001)
Shock × Post × Δ Non-Perf. Assets$_{t+1}$	-0.0002	-0.0003	0.0123***	0.0121***
	(0.0018)	(0.0018)	(0.0032)	(0.0032)
Shock × Post × Δ Non-Perf. Assets	0.0036**	0.0034*	0.0168***	0.0168***
	(0.0018)	(0.0018)	(0.0033)	(0.0033)
Shock × Post × Δ Non-Perf. Assets$_{t-1}$	0.0054***	0.0052***	0.0203***	0.0203***
	(0.0018)	(0.0018)	(0.0032)	(0.0032)
Shock × Post × Δ Non-Perf. Assets$_{t-2}$	-0.0014	-0.0016	0.0020	0.0020
	(0.0018)	(0.0018)	(0.0032)	(0.0033)
Shock × Post × EBP		0.0005		0.0193*
		(0.0069)		(0.0099)
Shock × Post × Tier1 Ratio$_{t-1}$		-0.0008***		0.0004
		(0.0002)		(0.0004)
Δ Non-Perf. Assets$_{t+1}$	0.0066***	0.0067***	-0.0012	-0.0012
	(0.0010)	(0.0010)	(0.0021)	(0.0021)
Δ Non-Perf. Assets	0.0184***	0.0185***	0.0312***	0.0312***
	(0.0010)	(0.0010)	(0.0021)	(0.0021)
Δ Non-Perf. Assets$_{t-1}$	0.0275***	0.0276***	0.0252***	0.0252***
	(0.0010)	(0.0010)	(0.0020)	(0.0020)
Δ Non-Perf. Assets$_{t-2}$	0.0243***	0.0244***	0.0339***	0.0339***
	(0.0010)	(0.0010)	(0.0021)	(0.0021)
EBP	0.2750***	0.2748***	0.2630***	0.2547***
	(0.0044)	(0.0050)	(0.0067)	(0.0079)
Tier1 Ratio$_{t-1}$	-0.0016***	-0.0013***	-0.0016***	-0.0017***
	(0.0002)	(0.0003)	(0.0004)	(0.0005)
Ln(Total Asset)$_{t-1}$	0.0003***	0.0003***	0.0002***	0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Δ Loan	-0.0044***	-0.0044***	-0.0048***	-0.0048***
	(0.0002)	(0.0002)	(0.0003)	(0.0003)
Resid'l RE Loan	-0.0005***	-0.0005***	-0.0013***	-0.0014***
	(0.0001)	(0.0001)	(0.0002)	(0.0002)
Comm'l & Indus'l Loan	0.0005***	0.0005***	-0.0011***	-0.0011***
	(0.0001)	(0.0001)	(0.0003)	(0.0003)
Comm'l RE Loan	-0.0017	-0.0017	-0.0036**	-0.0036**
	(0.0011)	(0.0011)	(0.0016)	(0.0016)
Constant	-0.0010***	-0.0010***	-0.0003	-0.0002
	(0.0002)	(0.0002)	(0.0003)	(0.0003)
Bank FE	Yes	Yes	Yes	Yes
State-Time FE	Yes	Yes	Yes	Yes
Observations	110367	110367	46749	46749
Adjusted R^2	0.38	0.38	0.57	0.57

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel B

	Small		Large	
	(1)	(2)	(3)	(4)
	Q4	Non-Q4	Q4	Non-Q4
Shock × Post	-0.0001	0.0001*	-0.0001	-0.0000
	(0.0001)	(0.0000)	(0.0002)	(0.0001)
Shock × Post × Δ Non-Perf. Assets$_{t+1}$	0.0086*	-0.0011	0.0054	0.0159***
	(0.0051)	(0.0018)	(0.0089)	(0.0034)
Shock × Post × Δ Non-Perf. Assets	0.0148***	0.0014	0.0354***	0.0081**
	(0.0048)	(0.0019)	(0.0083)	(0.0037)
Shock × Post × Δ Non-Perf. Assets$_{t-1}$	-0.0008	0.0068***	0.0211**	0.0215***
	(0.0051)	(0.0019)	(0.0085)	(0.0035)
Shock × Post × Δ Non-Perf. Assets$_{t-2}$	-0.0039	-0.0028	-0.0282***	0.0129***
	(0.0050)	(0.0019)	(0.0088)	(0.0035)
Shock × Post × EBP	0.0211	-0.0010	0.0447**	0.0100
	(0.0166)	(0.0075)	(0.0225)	(0.0110)
Shock × Post × Tier1 Ratio$_{t-1}$	-0.0006	-0.0008***	0.0007	0.0004
	(0.0006)	(0.0002)	(0.0010)	(0.0004)
Δ Non-Perf. Assets$_{t+1}$	0.0140***	0.0033***	-0.0001	-0.0050**
	(0.0029)	(0.0010)	(0.0059)	(0.0022)
Δ Non-Perf. Assets	0.0134***	0.0191***	0.0384***	0.0297***
	(0.0027)	(0.0011)	(0.0052)	(0.0023)
Δ Non-Perf. Assets$_{t-1}$	0.0357***	0.0251***	0.0341***	0.0212***
	(0.0029)	(0.0011)	(0.0053)	(0.0022)
Δ Non-Perf. Assets$_{t-2}$	0.0387***	0.0219***	0.0563***	0.0283***
	(0.0028)	(0.0011)	(0.0056)	(0.0022)
EBP	0.2813***	0.2672***	0.1340***	0.3275***
	(0.0114)	(0.0056)	(0.0170)	(0.0092)
Tier1 Ratio$_{t-1}$	-0.0025***	-0.0013***	-0.0025**	-0.0018***
	(0.0007)	(0.0003)	(0.0011)	(0.0005)
Ln(Total Asset)$_{t-1}$	0.0005***	0.0002***	0.0004***	0.0002***
	(0.0001)	(0.0000)	(0.0001)	(0.0000)
Δ Loan	-0.0084***	-0.0036***	-0.0091***	-0.0039***
	(0.0005)	(0.0002)	(0.0008)	(0.0003)
Resid'l RE Loan	-0.0007**	-0.0004***	-0.0016***	-0.0012***
	(0.0003)	(0.0001)	(0.0005)	(0.0002)
Comm'l & Indus'l Loan	0.0012***	0.0003*	-0.0004	-0.0012***
	(0.0004)	(0.0002)	(0.0006)	(0.0003)
Comm'l RE Loan	-0.0042	-0.0007	-0.0008	-0.0048***
	(0.0027)	(0.0011)	(0.0041)	(0.0017)
Constant	-0.0017***	-0.0007***	-0.0004	-0.0001
	(0.0006)	(0.0002)	(0.0008)	(0.0004)
Bank FE	Yes	Yes	Yes	Yes
State-Time FE	Yes	Yes	Yes	Yes
Observations	26582	82888	11188	35162
Adjusted R^2	0.40	0.37	0.54	0.58

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel C

	Small		Large	
	(1) Homogenous	(2) Heterogenous	(3) Homogenous	(4) Heterogenous
Shock × Post	-0.0001	0.0001	0.0000	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Shock × Post × Δ Non-Perf. Assets$_{t+1}$	-0.0053*	0.0034	0.0159***	0.0157***
	(0.0028)	(0.0024)	(0.0053)	(0.0043)
Shock × Post × Δ Non-Perf. Assets	0.0012	0.0049**	0.0158***	0.0180***
	(0.0028)	(0.0024)	(0.0056)	(0.0044)
Shock × Post × Δ Non-Perf. Assets$_{t-1}$	0.0062**	0.0049**	0.0167***	0.0228***
	(0.0028)	(0.0024)	(0.0052)	(0.0044)
Shock × Post × Δ Non-Perf. Assets$_{t-2}$	-0.0052*	-0.0005	0.0049	-0.0024
	(0.0028)	(0.0025)	(0.0052)	(0.0044)
Shock × Post × EBP	0.0056	0.0038	-0.0149	0.0385**
	(0.0097)	(0.0101)	(0.0138)	(0.0156)
Shock × Post × Tier1 Ratio$_{t-1}$	-0.0001	-0.0011**	0.0009*	-0.0003
	(0.0003)	(0.0004)	(0.0005)	(0.0008)
Δ Non-Perf. Assets$_{t+1}$	0.0059***	0.0066***	-0.0095***	0.0006
	(0.0015)	(0.0014)	(0.0034)	(0.0028)
Δ Non-Perf. Assets	0.0135***	0.0193***	0.0287***	0.0318***
	(0.0016)	(0.0014)	(0.0036)	(0.0028)
Δ Non-Perf. Assets$_{t-1}$	0.0244***	0.0273***	0.0239***	0.0229***
	(0.0016)	(0.0014)	(0.0033)	(0.0028)
Δ Non-Perf. Assets$_{t-2}$	0.0211***	0.0246***	0.0269***	0.0359***
	(0.0016)	(0.0014)	(0.0033)	(0.0028)
EBP	0.2533***	0.2902***	0.2967***	0.2467***
	(0.0073)	(0.0072)	(0.0114)	(0.0122)
Tier1 Ratio$_{t-1}$	-0.0009**	-0.0014***	-0.0002	-0.0027***
	(0.0003)	(0.0004)	(0.0006)	(0.0008)
Ln(Total Asset)$_{t-1}$	0.0005***	0.0002***	0.0003***	0.0003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Δ Loan	-0.0044***	-0.0040***	-0.0018***	-0.0063***
	(0.0003)	(0.0002)	(0.0004)	(0.0004)
Resid'l RE Loan	-0.0008***	0.0001	-0.0018***	0.0000
	(0.0002)	(0.0003)	(0.0003)	(0.0004)
Comm'l & Indus'l Loan	-0.0005*	0.0012***	-0.0012***	-0.0005
	(0.0003)	(0.0002)	(0.0004)	(0.0004)
Comm'l RE Loan	-0.0018	-0.0020	-0.0024	-0.0017
	(0.0016)	(0.0015)	(0.0027)	(0.0023)
Constant	-0.0015***	-0.0007**	-0.0008	-0.0007
	(0.0004)	(0.0003)	(0.0005)	(0.0005)
Bank FE	Yes	Yes	Yes	Yes
State-Time FE	Yes	Yes	Yes	Yes
Observations	49385	60162	20675	24931
Adjusted R^2	0.41	0.37	0.66	0.51

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

TABLE 6: This table presents the effect of Disaster on LLP based on banks' past experience with disasters. The sample includes banks that have been subject to a disaster in our sample period. *CumDisaster* is banks' disaster experience measured as the number of disasters the bank experienced in the past. Columns 1 to 3 measures from the beginning of our sample period. Columns 4 to 6 measures in the past 3 years. The dependent variable is banks' loan loss provisions in the current quarter scaled by lagged total loans. *Ln(Total Asset)* is the natural logarithm of total assets. *Tier1 Ratio* is the Tier 1 capital ratio of the bank. *EBP* is earnings before loan loss provisions and taxes. Δ *Loan* is the change in loans from last quarter to current quarter scaled by loans in last quarter. *Residential Real Estate Loan* is the ratio of residential real estate loans to total loans. *Commercial Real Estate Loan* is the ratio of commercial real estate loans to total loans. *Commercial and Industrial Loan* is the ratio of commerical and industrial loans to total loans. Δ *Non-Performing Assets* is banks' Non-performing Assets scaled by lagged total loans.

	All Past			Past 3 year		
	(1)	(2)	(3)	(4)	(5)	(6)
	Full	Big	Small	Full	Big	Small
CumDisaster	0.0000**	0.0000**	-0.0000	0.0000	0.0000	-0.0001**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
CumDisaster × Δ Non-Perf. Assets$_{t+1}$	0.0014***	0.0006	0.0012**	0.0034***	0.0023*	0.0009
	(0.0003)	(0.0004)	(0.0005)	(0.0008)	(0.0013)	(0.0012)
CumDisaster × Δ Non-Perf. Assets	0.0024***	0.0009**	0.0024***	0.0084***	0.0043***	0.0075***
	(0.0003)	(0.0004)	(0.0005)	(0.0009)	(0.0014)	(0.0013)
CumDisaster × Δ Non-Perf. Assets$_{t-1}$	0.0025***	0.0019***	0.0019***	0.0086***	0.0085***	0.0061***
	(0.0003)	(0.0004)	(0.0005)	(0.0009)	(0.0014)	(0.0013)
CumDisaster × Δ Non-Perf. Assets$_{t-2}$	0.0009***	0.0007*	-0.0002	0.0051***	0.0031**	0.0050***
	(0.0003)	(0.0004)	(0.0005)	(0.0009)	(0.0014)	(0.0014)
CumDisaster × EBP	-0.0000	0.0026**	-0.0007	0.0079***	0.0150***	0.0196***
	(0.0009)	(0.0012)	(0.0020)	(0.0030)	(0.0042)	(0.0051)
CumDisaster × Tier 1 Ratio$_{t-1}$	0.0000**	-0.0000*	0.0000***	-0.0000	-0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Δ Non-Perf. Assets$_{t+1}$	-0.0004	0.0065*	-0.0011	0.0002	0.0045	0.0027
	(0.0019)	(0.0039)	(0.0024)	(0.0021)	(0.0043)	(0.0026)
Δ Non-Perf. Assets	0.0138***	0.0374***	0.0085***	0.0101***	0.0331***	0.0066**
	(0.0019)	(0.0041)	(0.0025)	(0.0021)	(0.0046)	(0.0026)
Δ Non-Perf. Assets$_{t-1}$	0.0208***	0.0259***	0.0208***	0.0170***	0.0183***	0.0186***
	(0.0019)	(0.0040)	(0.0025)	(0.0022)	(0.0045)	(0.0027)
Δ Non-Perf. Assets$_{t-2}$	0.0177***	0.0238***	0.0178***	0.0128***	0.0208***	0.0092***
	(0.0019)	(0.0039)	(0.0025)	(0.0021)	(0.0044)	(0.0027)
EBP	0.2975***	0.2409***	0.3279***	0.2817***	0.2215***	0.2936***
	(0.0082)	(0.0146)	(0.0118)	(0.0089)	(0.0162)	(0.0120)
Tier 1 Ratio$_{t-1}$	-0.0000***	0.0000	-0.0000***	-0.0000*	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Ln(Total Asset)$_{t-1}$	0.0003***	0.0003***	0.0004***	0.0003***	0.0002***	0.0003***
	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0001)
Δ Loan	-0.0040***	-0.0042***	-0.0035***	-0.0039***	-0.0042***	-0.0034***
	(0.0002)	(0.0005)	(0.0003)	(0.0002)	(0.0005)	(0.0003)
Resid'l RE Loan	-0.0005***	-0.0021***	0.0003	-0.0004**	-0.0019***	0.0003
	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0003)
Comm'l & Indus'l Loan	0.0003	-0.0013***	0.0010***	0.0004*	-0.0012***	0.0011***
	(0.0002)	(0.0005)	(0.0003)	(0.0002)	(0.0004)	(0.0003)
Comm'l RE Loan	-0.0007	-0.0031	0.0030	0.0000	-0.0020	0.0032
	(0.0015)	(0.0028)	(0.0021)	(0.0015)	(0.0027)	(0.0021)
Constant	-0.0011***	-0.0005	-0.0020***	-0.0011***	-0.0003	-0.0017***
	(0.0003)	(0.0006)	(0.0005)	(0.0003)	(0.0006)	(0.0005)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	53723	18732	34410	53723	18732	34410
Adjusted R^2	0.48	0.58	0.41	0.48	0.58	0.42

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

TABLE 7: This table presents the effect of natural disaster on banks' lending. The dependent variable is bank's loan change from last quarter to 3 quarters later. Panel A presents on average how bank's loans change in the disaster period. Panel B measures banks' provision policy as the average residual in the past 12 quarters. Panel C measures banks' provision policy as the difference in R-squares between regression (1) $LLP_t = \alpha_0 + \alpha_1 \Delta NPA_{t-1} + \alpha_2 \Delta NPA_{t-2} + \alpha_3 Tier1Ratio_t + \alpha_4 EBP_t + e_t$ and regression (2) $LLP_t = \alpha_0 + \alpha_1 \Delta NPA_{t+1} + \alpha_2 \Delta NPA_t + \alpha_3 \Delta NPA_{t-1} + \alpha_4 \Delta NPA_{t-2} + \alpha_5 Tier1Ratio_t + \alpha_6 EBP_t + e_t$. All policy measures are dummy variables that equals one if the corresponding measure is higher than the median of all banks in the same quarter and same size group. *Shock* is a dummy variable, which is equal to 1 for banks that are affected by a disaster. *Post* is the dummy variable, which is equal to 1 from 0 to 3 quarters after a disaster. *Ln(Total Asset)* is the natural logarithm of total assets. *Tier1 Ratio* is the Tier 1 capital ratio of the bank. *EBP* is earnings before loan loss provisions and taxes. Δ *Loan* is the change in loans from last quarter to current quarter scaled by loans in last quarter. Δ *Non-Performing Assets* is banks' Non-performing Assets scaled by lagged total loans.

Panel A

	(1) Full	(2) Small	(3) Big
Shock × Post	0.0039***	0.0031***	0.0051**
	(0.0010)	(0.0011)	(0.0022)
EBP_{t-1}	1.5693***	1.0823***	1.2779**
	(0.2336)	(0.2687)	(0.5053)
Tier1 $Ratio_{t-1}$	0.0011***	0.0014***	0.0022***
	(0.0002)	(0.0002)	(0.0004)
Ln(Total $Asset)_{t-1}$	-0.0581***	-0.0794***	-0.0460***
	(0.0021)	(0.0031)	(0.0049)
Comm'l & Indus'l $Loan_{t-1}$	0.0900***	0.0543***	0.1367***
	(0.0078)	(0.0091)	(0.0203)
$Loan_{t-1}$	-0.2517***	-0.2875***	-0.2076***
	(0.0061)	(0.0071)	(0.0148)
$Deposit_{t-1}$	-0.0126	-0.0056	-0.0634***
	(0.0096)	(0.0123)	(0.0188)
Δ Non-Perf. $Assets_{t-1}$	-0.3656***	-0.3591***	-0.2807**
	(0.0421)	(0.0454)	(0.1103)
Constant	0.5206***	0.6277***	0.5126***
	(0.0170)	(0.0227)	(0.0432)
Observations	73327	56057	16545
Adjusted R^2	0.49	0.50	0.55

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel B - High Average Residual

	(1)	(2)	(3)	(4)	(5)	(6)
	Full	Small	Big	Full	Small	Big
HighRES12	-0.0209***	-0.0203***	-0.0207***	-0.0306***	-0.0328***	-0.0297***
	(0.0008)	(0.0009)	(0.0017)	(0.0021)	(0.0023)	(0.0048)
Shock × Post	0.0030***	0.0019*	0.0051**	0.0009	-0.0062**	0.0214***
	(0.0010)	(0.0012)	(0.0023)	(0.0024)	(0.0028)	(0.0055)
Shock × Post × HighRES12	0.0038**	0.0051***	-0.0013	-0.0069	0.0027	-0.0204*
	(0.0017)	(0.0019)	(0.0035)	(0.0044)	(0.0050)	(0.0108)
EBP_{t-1}	1.4968***	1.1013***	1.0671**	1.4697***	1.0943***	0.9900**
	(0.2322)	(0.2672)	(0.5022)	(0.2322)	(0.2671)	(0.5023)
Tier1 Ratio_{t-1}	0.0008***	0.0011***	0.0019***	0.0005***	0.0006***	0.0018***
	(0.0002)	(0.0002)	(0.0004)	(0.0002)	(0.0002)	(0.0004)
Ln(Total $\text{Asset})_{t-1}$	-0.0628***	-0.0875***	-0.0497***	-0.0628***	-0.0882***	-0.0498***
	(0.0021)	(0.0031)	(0.0049)	(0.0021)	(0.0031)	(0.0049)
Comm'l & Indus'l Loan_{t-1}	0.0863***	0.0496***	0.1334***	0.0868***	0.0499***	0.1337***
	(0.0078)	(0.0090)	(0.0201)	(0.0078)	(0.0090)	(0.0201)
Loan_{t-1}	-0.2562***	-0.2939***	-0.2103***	-0.2571***	-0.2953***	-0.2107***
	(0.0061)	(0.0071)	(0.0147)	(0.0061)	(0.0071)	(0.0147)
Deposit_{t-1}	-0.0087	0.0005	-0.0691***	-0.0074	0.0025	-0.0692***
	(0.0096)	(0.0123)	(0.0187)	(0.0096)	(0.0123)	(0.0187)
Δ Non-Perf. Assets_{t-1}	-0.4145***	-0.3978***	-0.3416***	-0.4136***	-0.3969***	-0.3370***
	(0.0419)	(0.0451)	(0.1096)	(0.0419)	(0.0451)	(0.1096)
Shock × Post × Tier1 Ratio_{t-1}				0.0001	0.0005***	-0.0012***
				(0.0001)	(0.0002)	(0.0004)
HighRES12 × Tier1 Ratio_{t-1}				0.0006***	0.0008***	0.0007**
				(0.0001)	(0.0001)	(0.0003)
Shock_t × Post_t × HighRES12 × Tier1 Ratio_{t-1}				0.0007***	0.0002	0.0014*
				(0.0003)	(0.0003)	(0.0008)
Constant	0.5574***	0.6820***	0.5548***	0.5617***	0.6912***	0.5569***
	(0.0170)	(0.0227)	(0.0431)	(0.0170)	(0.0227)	(0.0431)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	73327	56057	16545	73327	56057	16545
Adjusted R^2	0.50	0.51	0.55	0.50	0.51	0.55

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel C - High ΔR^2

	(1)	(2)	(3)	(4)	(5)	(6)
	Full	Small	Big	Full	Small	Big
HighR2	0.0007	0.0006	0.0020	-0.0017	-0.0025	-0.0058
	(0.0006)	(0.0007)	(0.0014)	(0.0017)	(0.0019)	(0.0042)
Shock × Post	0.0049***	0.0047***	0.0070***	0.0036	-0.0010	0.0223***
	(0.0012)	(0.0014)	(0.0026)	(0.0029)	(0.0034)	(0.0066)
Shock × Post × HighR2	-0.0020	-0.0031*	-0.0039	-0.0103***	-0.0099**	-0.0124
	(0.0014)	(0.0016)	(0.0030)	(0.0039)	(0.0045)	(0.0090)
EBP_{t-1}	1.5736***	1.0883***	1.2904**	1.5789***	1.0999***	1.2845**
	(0.2337)	(0.2688)	(0.5053)	(0.2337)	(0.2688)	(0.5052)
Tier1 Ratio_{t-1}	0.0011***	0.0014***	0.0022***	0.0010***	0.0012***	0.0020***
	(0.0002)	(0.0002)	(0.0004)	(0.0002)	(0.0002)	(0.0005)
$\text{Ln(Total Asset)}_{t-1}$	-0.0581***	-0.0794***	-0.0460***	-0.0581***	-0.0793***	-0.0462***
	(0.0021)	(0.0031)	(0.0049)	(0.0021)	(0.0031)	(0.0049)
Comm'l & Indus'l Loan_{t-1}	0.0899***	0.0541***	0.1362***	0.0898***	0.0541***	0.1349***
	(0.0078)	(0.0091)	(0.0203)	(0.0078)	(0.0091)	(0.0203)
Loan_{t-1}	-0.2517***	-0.2876***	-0.2076***	-0.2518***	-0.2879***	-0.2086***
	(0.0061)	(0.0071)	(0.0148)	(0.0061)	(0.0071)	(0.0148)
Deposit_{t-1}	-0.0128	-0.0058	-0.0635***	-0.0130	-0.0063	-0.0638***
	(0.0096)	(0.0123)	(0.0188)	(0.0096)	(0.0123)	(0.0188)
Δ Non-Perf. Assets_{t-1}	-0.3654***	-0.3590***	-0.2789**	-0.3658***	-0.3591***	-0.2838**
	(0.0421)	(0.0454)	(0.1103)	(0.0421)	(0.0454)	(0.1102)
Shock × Post × Tier1 Ratio_{t-1}				0.0001	0.0004*	-0.0011**
				(0.0002)	(0.0002)	(0.0004)
HighR2 × Tier1 Ratio_{t-1}				0.0002	0.0002*	0.0006*
				(0.0001)	(0.0001)	(0.0003)
Shock × Post × HighR2 × Tier1 Ratio_{t-1}				0.0006**	0.0004	0.0006
				(0.0002)	(0.0003)	(0.0006)
Constant	0.5205***	0.6276***	0.5115***	0.5228***	0.6311***	0.5164***
	(0.0170)	(0.0227)	(0.0433)	(0.0170)	(0.0227)	(0.0433)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	73327	56057	16545	73327	56057	16545
Adjusted R^2	0.49	0.50	0.55	0.49	0.50	0.55

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

TABLE 8: This table presents the effect of natural disaster on banks' lending by splitting the subsample as banks with high and low provision measure. The dependent variable is bank's loan change from last quarter to 3 quarters later. Panel A measures banks' provision policy as the average residual in the past 12 quarters. Panel B measures banks' provision policy as the difference in R-squares between regression (1) $LLP_t = \alpha_0 + \alpha_1 \Delta NPA_{t-1} + \alpha_2 \Delta NPA_{t-2} + \alpha_3 Tier1Ratio_t + \alpha_4 EBP_t + e_t$ and regression (2) $LLP_t = \alpha_0 + \alpha_1 \Delta NPA_{t+1} + \alpha_2 \Delta NPA_t + \alpha_3 \Delta NPA_{t-1} + \alpha_4 \Delta NPA_{t-2} + \alpha_5 Tier1Ratio_t + \alpha_6 EBP_t + e_t$. All policy measures are dummy variables that equals one if the corresponding measure is higher than the median of all banks in the same quarter and same size group. *Shock* is a dummy variable, which is equal to 1 for banks that are affected by a disaster. *Post* is the dummy variable, which is equal to 1 from 0 to 3 quarters after a disaster. *Ln(Total Asset)* is the natural logarithm of total assets. *Tier1 Ratio* is the Tier 1 capital ratio of the bank. *EBP* is earnings before loan loss provisions and taxes. Δ *Loan* is the change in loans from last quarter to current quarter scaled by loans in last quarter. Δ *Non-Performing Assets* is banks' Non-performing Assets scaled by lagged total loans.

Panel A – Residual provision as the Measure of Provision Policy

	Full		Small		Large	
	(1) High Prov'n	(2) Low Prov'n	(3) High Prov'n	(4) Low Prov'n	(5) High Prov'n	(6) Low Prov'n
Shock × Post	-0.0097***	0.0014	-0.0100***	-0.0035	0.0098	0.0194***
	(0.0030)	(0.0031)	(0.0034)	(0.0036)	(0.0079)	(0.0072)
Tier1 Ratio$_{t-1}$	0.0015***	0.0001	0.0014***	0.0004	0.0049***	0.0002
	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0006)	(0.0008)
Shock × Post × Tier1 Ratio$_{t-1}$	0.0009***	-0.0001	0.0010***	0.0003	-0.0004	-0.0017***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0005)	(0.0005)
EBP$_{t-1}$	1.9878***	-0.3531	1.5348***	-0.4121	1.1914*	0.7072
	(0.2921)	(0.4199)	(0.3395)	(0.4721)	(0.6299)	(1.0567)
Ln(Total Asset)$_{t-1}$	-0.0672***	-0.0742***	-0.0999***	-0.1190***	-0.0741***	-0.0213***
	(0.0033)	(0.0036)	(0.0047)	(0.0054)	(0.0086)	(0.0081)
Comm'l & Indus'l Loan$_{t-1}$	0.0784***	0.0564***	0.0423***	0.0266*	0.1793***	0.0412
	(0.0117)	(0.0128)	(0.0131)	(0.0152)	(0.0388)	(0.0330)
Loan$_{t-1}$	-0.2822***	-0.3231***	-0.3304***	-0.3547***	-0.2198***	-0.2845***
	(0.0090)	(0.0095)	(0.0104)	(0.0113)	(0.0235)	(0.0250)
Deposit$_{t-1}$	0.0445***	-0.0308**	0.0372*	-0.0009	-0.0033	-0.1420***
	(0.0150)	(0.0139)	(0.0192)	(0.0177)	(0.0312)	(0.0304)
Δ Non-Perf. Assets$_{t-1}$	-0.2968***	-0.4258***	-0.3006***	-0.4261***	-0.0385	-0.1608
	(0.0511)	(0.0736)	(0.0553)	(0.0795)	(0.1368)	(0.2100)
Constant	0.5271***	0.7158***	0.7176***	0.9203***	0.6144***	0.5141***
	(0.0257)	(0.0276)	(0.0342)	(0.0376)	(0.0748)	(0.0706)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	39539	32921	30092	25107	8466	6828
Adjusted R^2	0.56	0.50	0.58	0.51	0.62	0.54

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel B – R-Square Difference as the Measure of Provision Policy

	Full		Small		Large	
	(1) High Prov'n	(2) Low Prov'n	(3) High Prov'n	(4) Low Prov'n	(5) High Prov'n	(6) Low Prov'n
Shock × Post	-0.0086***	0.0056*	-0.0133***	0.0010	0.0162**	0.0250***
	(0.0031)	(0.0032)	(0.0035)	(0.0037)	(0.0082)	(0.0076)
Tier1 Ratio$_{t-1}$	0.0007***	0.0012***	0.0010***	0.0015***	0.0026***	0.0032***
	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0007)	(0.0007)
Shock × Post × Tier1 Ratio$_{t-1}$	0.0008***	-0.0001	0.0009***	0.0002	-0.0007	-0.0014***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0005)	(0.0005)
EBP$_{t-1}$	2.4289***	0.6444*	1.8008***	0.6816*	1.9909**	-0.6282
	(0.3421)	(0.3416)	(0.3905)	(0.3991)	(0.8100)	(0.7552)
Ln(Total Asset)$_{t-1}$	-0.0529***	-0.0647***	-0.0695***	-0.0923***	-0.0557***	-0.0397***
	(0.0033)	(0.0032)	(0.0046)	(0.0048)	(0.0083)	(0.0077)
Comm'l & Indus'l Loan$_{t-1}$	0.0723***	0.1130***	0.0299**	0.0869***	0.0485	0.2058***
	(0.0119)	(0.0118)	(0.0139)	(0.0136)	(0.0332)	(0.0336)
Loan$_{t-1}$	-0.2901***	-0.2407***	-0.3273***	-0.2865***	-0.2898***	-0.1830***
	(0.0092)	(0.0091)	(0.0107)	(0.0109)	(0.0242)	(0.0229)
Deposit$_{t-1}$	-0.0268*	0.0093	-0.0108	0.0134	-0.0939***	-0.0098
	(0.0145)	(0.0143)	(0.0188)	(0.0184)	(0.0299)	(0.0301)
Δ Non-Perf. Assets$_{t-1}$	-0.4687***	-0.2585***	-0.4387***	-0.2829***	-0.5399***	-0.1727
	(0.0600)	(0.0611)	(0.0645)	(0.0667)	(0.1738)	(0.1637)
Constant	0.5315***	0.5328***	0.6099***	0.6783***	0.6635***	0.3891***
	(0.0257)	(0.0255)	(0.0339)	(0.0349)	(0.0716)	(0.0684)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	36161	35996	27571	27420	7611	7634
Adjusted R^2	0.53	0.52	0.55	0.53	0.59	0.59

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

A Appendix

A.1 Variable Definitions

TABLE A.1: This table reports the variable definitions and the call report item.

Variable	Call Report Item
Total Asset	RCFD2170
Deposit	RCFD2200
LLP	RIAD4230
Tier1 Ratio	RCFD8274
Resid'l RE Loan	(RCON1797 + RCON5367 + RCFD5368 + RCFD1460)
Comm'l & Indus'l Loan	RCFD1766
Comm'l RE Loan	RCFD2746
EBP	(RIAD4300 + RIAD4230)
Loan	RCFD2122
Non-Perf. Assets	(RCFD1403 + RCFD1407)

A.2 Supplementary Tables and Figures

TABLE A.2: This table presents the effect of Disaster on LLP. Panel A of this table shows the average effect of disaster on banks' loan loss provisioning. Panel B shows how banks adjust the weight of their non–performing assets on their loan loss provisioning during natural disaster period. The dependent variable is banks' loan loss provisions in the current quarter scaled by lagged total loans. *Shock* is a dummy variable, which is equal to 1 for banks that are affected by a disaster. *Post* is the dummy variable, which is equal to 1 from 0 to 3 quarters after a disaster. *Ln(Total Asset)* is the natural logarithm of total assets. *EBP* is earnings before loan loss provisions and taxes. *Tier1 Ratio* is the Tier 1 capital ratio of the bank. Δ *Loan* is the change in loans from last quarter to current quarter scaled by loans in last quarter. *Residential Real Estate Loan* is the ratio of residential real estate loans to total loans. *Commercial Real Estate Loan* is the ratio of commercial real estate loans to total loans. *Commercial and Industrial Loan* is the ratio of commerical and industrial loans to total loans. Δ *Non-Performing Assets* is banks' Non-performing Assets scaled by lagged total loans.

	(1) LLP	(2) LLP	(3) LLP	(4) LLP	(5) LLP
Shock × Post	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Ln(Total Asset)$_{t-1}$	0.0004***	0.0004***	0.0002***	0.0003***	0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Tier1 Ratio$_{t-1}$	-0.0021***	-0.0019***	-0.0017***	-0.0019***	-0.0016***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
EBP	0.2640***	0.2748***	0.2523***	0.2568***	0.2658***
	(0.0037)	(0.0036)	(0.0036)	(0.0036)	(0.0036)
Δ Loan	-0.0061***	-0.0050***	-0.0058***	-0.0055***	-0.0048***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Resid'l RE Loan	-0.0010***	-0.0009***	-0.0007***	-0.0007***	-0.0007***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Comm'l & Indus'l Loan	-0.0003***	-0.0001	-0.0002*	-0.0003***	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Comm'l RE Loan	-0.0005	-0.0019**	-0.0006	-0.0008	-0.0018**
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Δ Non-Perf. Assets$_{t+1}$			0.0102***	0.0103***	0.0070***
			(0.0007)	(0.0007)	(0.0007)
Δ Non-Perf. Assets			0.0289***	0.0288***	0.0246***
			(0.0008)	(0.0008)	(0.0008)
Δ Non-Perf. Assets$_{t-1}$			0.0370***	0.0367***	0.0317***
			(0.0008)	(0.0008)	(0.0008)
Δ Non-Perf. Assets$_{t-2}$			0.0329***	0.0327***	0.0280***
			(0.0008)	(0.0008)	(0.0008)
House Index				-0.0000***	
				(0.0000)	
Δ GDP				-0.0000***	
				(0.0000)	
Δ Unemployment				0.0002***	
				(0.0000)	
Constant	-0.0012***	-0.0012***	-0.0004***	0.0014***	-0.0006***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Bank FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	Yes	No
State-Time FE	No	Yes	No	No	Yes
Observations	157788	157689	157772	157772	157673
Adjusted R^2	0.38	0.42	0.40	0.41	0.44

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$